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SOCIO-TECHNICAL SYSTEMS SUPPORTING HEALTHY FOOD DECISIONS

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ABSTRACT

The increasing availability of cheap and fast computational resources allows for technology to provide in-time support in various life decisions. To improve everyday nutrition decision, socio-technical systems, such as mobile applications, can provide individual users with useful knowledge about nutrition, motivational support, as well as suggestions and feedback on situational and general behavior. Regarding the human interface, this work uses concepts such as serious games, persuasive systems, visualization techniques, and recommender systems to appropriately address different aspects of nutrition decisions. As for the technical aspects, an application needs to model the users' profiles, their context, and the attributes of available food choices.
The requirements for healthy nutrition interventions on children lead to a focus on serious games for healthy nutrition. Two systems were developed and evaluated according to the design science research cycles. The NUDGE platform design provides a personalized avatar, a social network, and a mini-game collection. We show in a controlled study with 61 participants that the avatar concept can be beneficial to physical activity behavior depending on the perceived movement competence of the participants. The study further revealed that the avatar concept on its own was not perceived to provide sufficient variety and fun. This insight leads to the second design cycle focussing on the serious games for healthy nutrition "Fit, Food, Fun". After several design iterations and validations, the game was evaluated in another controlled study with 72 participants. The study shows that the developed game is increasing knowledge similar to a teaching control group. We further provide a detailed analysis of the mediating factors of the study, such as personality and motivational attributes of the participants and their behavior inside the game. This analysis shows that the success of a serious game is dependent on the study sample and thus needs to be more personalized and adaptable.
The requirements for healthy nutrition interventions on adults lead to a focus on personalized nutrition recommendations, and persuasive feedback applications. The mobile application Nutrilize was designed and evaluated in multiple iterations, followed by a pilot study with 14 participants over the course of three weeks. The final system was evaluated with both a short-term study of 98 participants over two weeks and a long-term study of 34 participants over either 8 or 12 weeks. The days spent in the study significantly influence optimal nutrient intake in the long-term study, but not in the short-term study, while other covariant effects are similar between both studies. In the short-term study, we additionally observe ability personalization leading to better-perceived diversity, personalization and system effectiveness. The long-term study additionally revealed dropout issues due to stress, social pressure, and tracking effort. Furthermore, visual feedback is both perceived well and effective in improving the users' behavior, while recommendations are not always trusted to improve health and criticized for not fitting the users' context-dependent requirements. Finally, missing automation of dietary tracking leads to a lack of accuracy compared to the FFQ measures and is propagating errors to the feedback and recommendations of the system.

Overall, both focus areas show positive results for using socio-technical systems to improve the knowledge, motivation and behavior of their users towards healthier nutrition. The limiting factors derived are perceived deficiencies in terms of medical and psychological personalization, context awareness, and automation regarding the data collection.

KURZFASSUNG

Die zunehmende Verfügbarkeit von günstigen und schnellen Rechenressourcen ermöglicht es der Technologie, bei verschiedenen Lebensentscheidungen zeitnahe Unterstützung zu leisten. Um die alltäglichen Ernährungsentscheidungen zu verbessern, können soziotechnische Systeme, z.B. mobile Anwendungen, den einzelnen Nutzern nützliches Wissen über Ernährung, Motivationsunterstützung, sowie Vorschläge und Rückmeldungen zu situativem und allgemeinem Verhalten liefern. In Bezug auf die menschliche Schnittstelle verwendet diese Arbeit Konzepte wie Serious Games, Persuasive Feedback, Visualisierungstechniken und Empfehlungssysteme, um verschiedene Aspekte von Ernährungsentscheidungen angemessen zu adressieren. Was die technischen Aspekte anbelangt, so muss eine Anwendung die Profile der Nutzer, ihren Kontext und die Eigenschaften der verfügbaren Lebensmittel modellieren.
Die Anforderungen an Interventionen im Bereich der gesunden Ernährung bei Kindern führen dazu, dass der Schwerpunkt auf ernsthafte Spiele für gesunde Ernährung gelegt wird. Entsprechend den Forschungszyklen der Designwissenschaften wurden zwei Systeme entwickelt und evaluiert. Das Design der NUDGE-Plattform bietet einen personalisierten Avatar, ein soziales Netzwerk und eine Sammlung von Minispielen. Wir zeigen in einer kontrollierten Studie mit 61 Teilnehmern, dass das Avatarkonzept je nach der wahrgenommenen Bewegungskompetenz der Teilnehmer für das Bewegungsverhalten vorteilhaft sein kann. Die Studie ergab ferner, dass das Avatarkonzept allein nicht als ausreichend abwechslungsreich und unterhaltsam empfunden wurde. Diese Erkenntnis führt dazu, dass sich der zweite Designzyklus auf ein Serious Games für gesunde Ernährung "Fit, Food, Fun"konzentriert. Nach mehreren Design-Iterationen und Validierungen wurde das Spiel in einer weiteren kontrollierten Studie mit 72 Teilnehmern evaluiert. Die Studie zeigt, dass das entwickelte Spiel den Wissensstand ähnlich wie in der Lehrkontrollgruppe erhöht. Darüber hinaus liefern wir eine detaillierte Analyse der vermittelnden Faktoren der Studie, wie z.B. Persönlichkeits- und Motivationsattribute der Teilnehmer und ihr Verhalten im Spiel. Diese Analyse zeigt, dass der Erfolg eines Serious Games von der Studienprobe abhängt und daher personalisierter und anpassungsfähiger sein muss.
Die Anforderungen an Interventionen im Bereich der gesunden Ernährung bei Erwachsenen führen dazu, dass der Schwerpunkt auf personalisierte Ernährungsempfehlungen und Persuasive Feedback-Anwendungen. Die mobile Anwendung Nutrilize wurde in mehreren Iterationen entworfen und evaluiert, gefolgt von einer Pilotstudie mit 14 Teilnehmern über drei Wochen. Das endgültige System wurde sowohl in einer Kurzzeitstudie mit 98 Teilnehmern über zwei Wochen als auch mit einer Langzeitstudie mit 34 Teilnehmern über 8 oder 12 Wochen evaluiert. Die in der Studie verbrachten Tage beeinflussen die optimale Nährstoffaufnahme in der Langzeitstudie, aber nicht in der Kurzzeitstudie, während andere Nebeneffekte zwischen beiden Studien ähnlich sind. In der Kurzzeitstudie beobachten wir zusätzlich, dass eine Personalisierung nach Fähigkeiten zu einer besser wahrgenommenen Vielfalt, Personalisierung und Systemeffektivität führt. Die Langzeitstudie zeigte zusätzlich Abbruchprobleme aufgrund von Stress, sozialem Druck und Dateneingabeaufwand.

Darüber hinaus wird visuelles Feedback als gut und effektiv zur Verbesserung des Nutzerverhaltens wahrgenommen, während Empfehlungen nicht immer als gesundheitsfördernd empfunden werden und kritisiert werden, weil sie nicht den kontextabhängigen Anforderungen der Nutzer entsprechen. Schließlich führt die fehlende Automatisierung der Ernährungseingabe zu einem Mangel an Genauigkeit im Vergleich zu den FFQ-Messungen und verbreitet Fehler in den Rückmeldungen und Empfehlungen des Systems.
Insgesamt zeigen beide Schwerpunktbereiche positive Ergebnisse für den Einsatz soziotechnischer Systeme zur Verbesserung des Wissens, der Motivation und des Verhaltens ihrer Nutzer in Bezug auf eine gesündere Ernährung. Als begrenzende Faktoren werden Defizite in Bezug auf die medizinische und psychologische Personalisierung, das Kontextbewusstsein und die Automatisierung der Datenerhebung abgeleitet.

PRIOR PUBLICATIONS

Holzmann, S., Dischl, F., Schäfer, H., Plecher, D., Klinker, G., Groh, G., Hauner, H., and Holzapfel, C. (2017). Ergebnisse einer Befragung von Jugendlichen zu deren Wünschen, Motiven und Bedürfnissen im Hinblick auf Ernährungskommunikation und digitales Spielen. In *DGE Kongress, Kiel, Germany*.

Holzmann, S., Schäfer, H., Terzimehić, N., Leipold, N., Navickas, L., Böhm, M., Groh, G., Krcmar, H., Hauner, H., and Holzapfel, C. (2018). "The Wisdom of Crowds"-Survey: Digitale Bewertung von Mahlzeitenfotos nach nährwertspezifischen Kriterien. In *DGE Kongress, Stuttgart, Germany*.

Holzmann, S. L., Dischl, F., Schäfer, H., Groh, G., Hauner, H., and Holzapfel, C. (2019a). Digital Gaming for Nutritional Education: A Survey on Preferences, Motives, and Needs of Children and Adolescents. *JMIR Form Res*, 3(1):e10284, ISSN: 2561-326X, DOI: 10.2196/10284, http://formative.jmir.org/2019/1/e10284/.

Holzmann, S. L., Schäfer, H., Groh, G., Plecher, D. A., Klinker, G., Schauberger, G., Hauner, H., and Holzapfel, C. (2019b). Short-Term Effects of the Serious Game "Fit, Food, Fun" on Nutritional Knowledge: A Pilot Study among Children and Adolescents. *Nutrients*, 11(9):2031.

Holzmann, S. L., Schäfer, H., Plecher, D. A., Stecher, L., Klinker, G. J., Groh, G., Hauner, H., and Holzapfel, C. (2020). Serious Games for Nutritional Education: Online Survey on Preferences, Motives, and Behaviors Among Young Adults at University. *JMIR Serious Games*, 8(2):e16216, ISSN: 2291-9279, DOI: 10.2196/16216, https://games.jmir.org/2020/2/e16216.

Leipold, N., Madenach, M., Schäfer, H., Lurz, M., Terzimehić, N., Groh, G., Böhm, M., Gedrich, K., and Krcmar, H. (2018). Nutrilize a Personalized Nutrition Recommender System: an enable study. In *Proceedings of the 3rd International Workshop on Health Recommender Systems (HealthRecSys'18) co-located with the 12th ACM Conference on Recommender Systems (ACM RecSys 2018)*.

Madenach, M., Schäfer, H., Leipold, N., Böhm, M., Groh, G., Gedrich, K., and Daniel, H. (2017). Smartphone-app with Automated Personalized Nutrition Recommendations - Results from a Pilot Study -. In *Max Rubner Conference 2017: Nutrition Monitoring - Challenges and Developments*.

Sailer, M., Schäfer, H., and Groh, G. (2017). Group Motivation for Social Games. In Burghardt, M., Wimmer, R., Wolff, C., and Womser-Hacker, C., editors, *Mensch und Computer 2017 - Tagungsband*, pages 351–354, Regensburg. Gesellschaft f¸r Informatik e.V.

Schäfer, H. (2016). Personalized Support for Healthy Nutrition Decisions. In *Proceedings of the 10th ACM Conference on Recommender Systems*, RecSys '16, pages 455–458, New York, NY, USA. ACM, ISBN: 978-1-4503-4035-9, DOI: 10.1145/2959100.2959105, http://doi.acm.org/10.1145/2959100.2959105.

Schäfer, H., Bachner, J., Pretscher, S., Groh, G., and Demetriou, Y. (2018). Study on Motivating Physical Activity in Children with Personalized Gamified Feedback. In *Adjunct Publication of the 26th Conference on User Modeling, Adaptation and Personalization*, UMAP '18, pages 221–226, New York, NY, USA. ACM, ISBN: 978-1-4503-5784-5, DOI: 10.1145/3213586.3225227, http://doi.acm.org/10.1145/3213586.3225227.

Schäfer, H., Elahi, M., Elsweiler, D., Groh, G., Harvey, M., Ludwig, B., Ricci, F., and Said, A. (2017a). User Nutrition Modelling and Recommendation: Balancing Simplicity and Complexity. In *Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization*, UMAP '17, pages 93–96, New York, NY, USA. ACM, ISBN: 978-1-4503-5067-9, DOI: 10.1145/3099023.3099108, http://doi.acm.org/10.1145/3099023.3099108.

Schäfer, H., Groh, G., Plecher, D., Klinker, G., Madenach, M., Gedrich, K., Terzimehić, N., Leipold, N., and Böhm, M. (2016). Smart Personalized Nutrition aus der Perspektive soziotechnischer Systeme. *FoodLab Magazin*. http://www.blmedien.de/data/emags/blmedien/FOOD-Lab_04_2016/pubData/mobile/index.htm.

Schäfer, H., Groh, G., Schlichter, J., Kolossa, S., Daniel, H., Hecktor, R., and Greupner, T. (2015). Personalized Food Recommendation. In *Proceedings of the 2nd International Workshop on Decision Making and Recommender Systems*.

Schäfer, H., Hors-Fraile, S., Karumur, R. P., Calero Valdez, A., Said, A., Torkamaan, H., Ulmer, T., and Trattner, C. (2017b). Towards Health (Aware) Recommender Systems. In *Proceedings of the 2017 International Conference on Digital Health*, DH '17, pages 157–161, New York, NY, USA. ACM, ISBN: 978-1-4503-5249-9, DOI: 10.1145/3079452.3079499, http://doi.acm.org/10.1145/3079452.3079499.

Schäfer, H., Plecher, D., Holzmann, S., Groh, G., Klinker, G., Holzapfel, C., and Hauner, H. (2017). NUDGE - NUtritional, Digital Games in Enable. In *POSITIVE GAMING - Workshop on Gamification and Games for Wellbeing - Co-located with CHIPlay 2017*.

Schäfer, H. and Willemsen, M. C. (2019). Rasch-based Tailored Goals for Nutrition Assistance Systems. In *Proceedings of the 24th International Conference on Intelligent User Interfaces*, IUI '19, pages 18–29, New York, NY, USA. ACM, ISBN: 978-1-4503-6272-6, DOI: 10.1145/3301275.3302298, http://doi.acm.org/10.1145/3301275.3302298.

Terzimehić, N., Leipold, N., Schäfer, H., Madenach, M., Böhm, M., Groh, G., and Gedrich, K. (2016). Can an Automated Personalized Nutrition Assistance System Successfully Change Nutrition Behavior?-Study Design. In *Proceedings of the International Conference on Information Systems (ICIS) 2016*.

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LIST OF ABBREVIATIONS

AIC	Akaike information criterion
BBN	Bayesian Belief Networks
BCTS	Behavioral Change Techniques
BFI10	10-item Big Five Inventory
BIC	Bayesian information criterion
BLS	Bundeslebensmittelschlüssel
BMI	Body-Mass-Index
BMR	Basal Metabolic Rate
BWMPs	Behavioral Weight Management Programs
CFA	Confirmatory Factor Analysis
DBS	Dried Blood Spots
DGE	Deutsche Gesellschaft für Ernährung e.V.
DHI	Digital Health Intervention
DRI	Dietary Reference Intake
EAR	Estimated Average Requirement
FFQ	Food Frequency Questionnaire
G4H	Games for Health
HC	Hill Climbing
HEI	Healthy Eating Index
HKV	implicit matrix factorization method by Hu, Koren, and Volinsky
HRS	Health-Recommender-System
IMI	Intrinsic Motivation Inventory
Inter.IAMB	Interleaved Incremental Association Learning Algorithm
kCal	Kilocalories
LogLik	Log-Likelihood
MAP	Mean Average Precision
MET	Metabolic Equivalent of Task
MUFA	Mono-Unsaturated-Fatty-Acids
MVPA	Moderate- to Vigorous-Intensity Physical Activity

NDCG	Normalized Discounted Cumulative Gain
PAL	Physical Activity Level
PA	Physical Activity
PSD	Persuasive System Design
PUFA	Poly-Unsaturated-Fatty-Acids
RCTs	Randomized Controlled Trials
RDA	Recommended Daily Allowance
REML	Restricted Maximum Likelihood
s.e.	Standard Error
SDT	Self Determination Theory
SEM	Structural Equation Modelling
SFA	Saturated-Fatty-Acids
STPS	Susceptibility to Persuasion Scale
SUS	System Usability Scale
T2DM	Type 2 Diabetis Mellitus
TAM	Technology Acceptance Model
TEE	Total Energy Expenditure
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
TSRQ	Treatment SelfRegulation Questionnaire
UEQ	User Experience Questionnaire
UL	Upper Limit
USDA	U.S. Department of Agriculture
WHO	World Health Organization
WHR	Waist-Hip-Ratio

Part I

FOUNDATIONS

1

INTRODUCTION

This chapter motivates the research question of this thesis through the need for better nutrition on a global scale. The motivation section argues how socio-technical systems can serve as a scalable and low-cost solution that provides automated, personalized nutrition advice within easily understandable interfaces that improve users' long-term engagement. The chapter further defines the overarching research questions on how such socio-technical systems can reach these goals and finally support healthier food choices via knowledge, motivation, behavior, and despite the challenges of real-life contexts. We discuss how we apply Hevner's design science methodology for each of the seven guidelines (Hevner et al., 2004) and how we structure the iterative design and evaluation of our socio-technical systems within its three cycles (Hevner, 2007): rigor, design, and evaluation. The structure of this thesis is split into two parts: one for children and one for adults. Each chapter aligns with one of the research cycles within the scope of each part. Finally, as suggested by the seventh guideline, our research results have been communicated in several publications whose contribution to the chapters is discussed at the end of this introduction chapter.

1.1 INTRODUCTION AND MOTIVATION

One of the significant burdens of modern society is the risk of non-communicable diseases. According to the World Health Organization (WHO) report 2017 (WHO, 2017b), non-communicable diseases are estimated to account for 91% of deaths in Germany. The highest risk factors leading to these non-communicable diseases in Germany are listed as "physical inactivity", "raised blood pressure", "tobacco use", and "obesity" (WHO, 2017b). One way to reduce the impact of these risk factors (e.g., high blood pressure, obesity) is to improve the general population's nutrition. There are three major impediments to the long-term implementation of healthy nutrition: missing knowledge on healthy nutrition, missing motivation for dietary change, contextual constraints to nutrition behavior. Traditional measures to counteract these impediments are educational programs to bring nutritional knowledge into schools or even to adults, dieticians to motivate and guide the dietary change of a person, and political programs providing access to healthy nutrition, e.g., in canteens. All these measures are subject to high costs and are limited in scalability due to the personnel's availability. A scalable and low-cost way to bring healthy nutrition to a high percentage of the population is the implementation of intelligent applications that support gain in nutrition knowledge, motivational support, and advice on the user's daily dietary decisions. However, such applications are not fully explored yet and suffer from several shortcomings. First, for the applications to work independently, the nutritional knowledge needs to be formalized. Most guidelines are, however, population-based and not readily applicable to a specific user. Thus, new formalized nutrition models taking the user's nutritional context into account need to be implemented. Secondly, healthy nutrition is a very complex problem with multiple interdependent influence factors. This complexity can lead to applications becoming overwhelming for the user and difficult to understand. Two ways in which these effects can be counteracted are personalized visual feedback and recommendations. Third, digital applications, especially in the area of health, often suffer from high dropout rates. Related research suggests both gamified and persuasive design for counteracting the motivational loss and thus increase long-term engagement in such applications. This thesis is funded by the interdisciplinary *enable* cluster, one of four clusters about nutrition research funded by the German Federal Ministry of Education and Research (BMBF) (enable cluster, 2020).

1.2 PROBLEM STATEMENT AND RESEARCH QUESTIONS

This thesis focusses on socio-technical systems supporting healthy food decisions by developing design variations of such systems according to the design science research cycle. The overall problem statement is:

> How can socio-technical systems support healthier food choices?

This problem statement leads to the following research questions which are addressed in the subsequent chapters.

RQ 1: How can personalized socio-technical systems be designed to support nutritional knowledge?

RQ 2: How can personalized socio-technical systems be designed to support nutritional motivation?

RQ 3: How can personalized socio-technical systems be designed to support nutritional behavior?

RQ 4: What are the limitations of personalized socio-technical systems in real-life contexts?

1.3 RESEARCH METHODOLOGY

For the given problem statement of how socio-technical systems can support healthier food choices and subsequent research questions, a suitable research methodology is the design science research methodology. Design science focuses on creating and improving design artifacts such as socio-technical systems in a constructive research process. Its goal is to iteratively understand and adjust a domain problem and its artifact solution. For this methodology, Hevner et al. (Hevner et al., 2004) provide a list of guidelines. We address these guidelines in the following manner:

Guideline 1: We follow the *Design as an Artifact* guideline by providing different artifacts of socio-technical systems for healthy nutrition that are designed, revised and studied in their target context.

Guideline 2: We follow the *Problem Relevance* guideline by discussing related work on nutrition interventions, existing applications, and previous methods used in socio-technical systems for healthy nutrition.

Guideline 3: We follow the *Design Evaluation* guideline by evaluating each of our artifacts in both qualitative and quantitative manner.

Guideline 4: We follow the *Research Contributions* guideline by extracting valuable conclusions on the design of socio-technical systems for health behavior from the evaluation of our artifacts on healthy nutrition. Chapter 12 provides a discussion of the research contributions.

Guideline 5: We follow the *Research Rigor* guideline by application of established methodologies in the research field and iterative evaluation and reassessment of the artifacts. Specifically, we use literature and market analyses to provide the interdisciplinary requirements in chapter 2. We further use usability tests, think-aloud protocols, focus groups, and user studies for the design iterations in chapter 3, 5, 7, and 8. We finally use both short-term and long-term between- and within-subject controlled trials in chapter 4, 6, 9, and 10 to understand the effects of our artifacts in the field.

Guideline 6: We follow the *Design as a Search Process* guideline by iteratively refining and validating the artifacts and entering them into field evaluations.

Guideline 7: We follow the *Communication of Research* guideline by sharing our results in scientific publications. A complete list of publications is given at the beginning of this thesis.

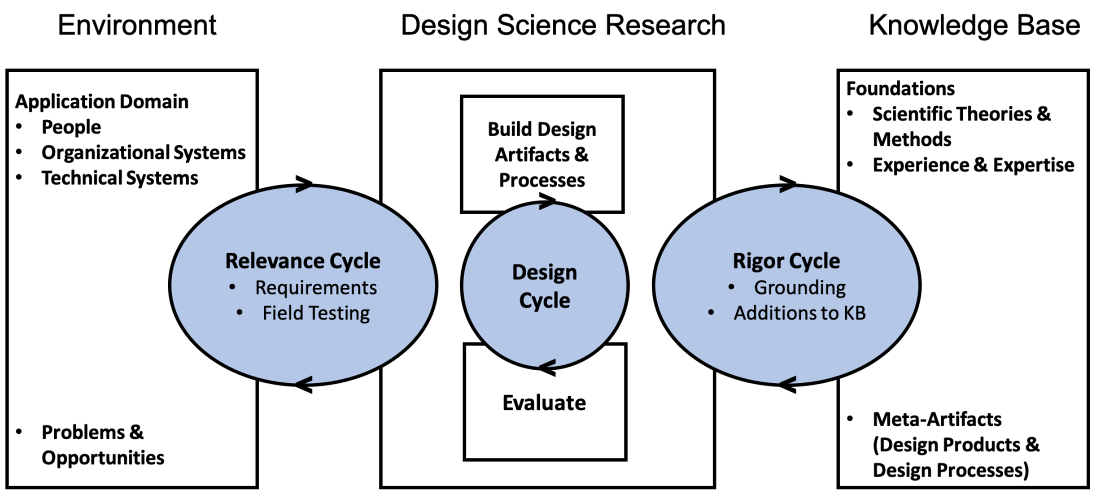


Figure 1: The three Cycles of Design Science: Relevance, Design, and Rigor. The rigor cycle connects the design artifact to the theoretical foundations of prior science. The design cycle iteratively builds and evaluates the design artifact. The relevance cycle connects the design artifact to its target environment. The figure has been adapted from (Hevner, 2007).

In his more recent work, Hevner furthermore defines how design science research is structured in three separate research cycles (Hevner, 2007). We thus shortly elaborate on how these cycles (figure 1) are incorporated in this thesis.

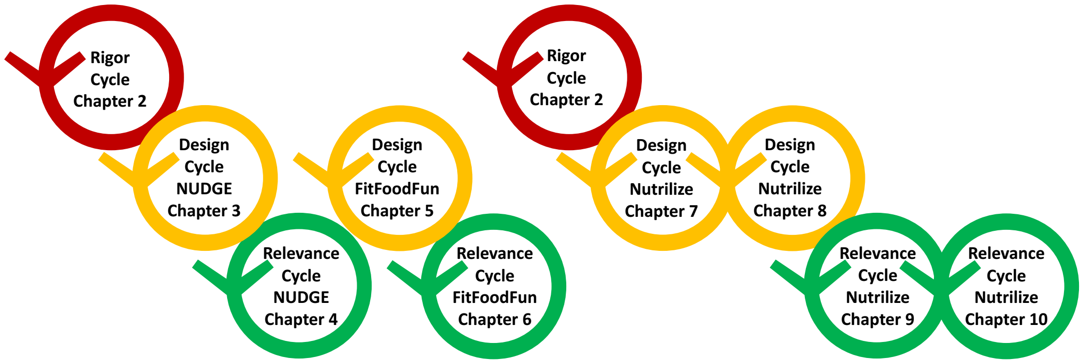


Figure 2: Application of the three cycles of design science in this thesis on the case of nutritional games for young adults (left) and the case of nutrition assistance systems for adults (right).

Figure 2 illustrates how these cycles were traversed in both parts of this thesis. The first chapter (chapter 2) focuses on integrating existing knowledge-bases into our designs and represents our activities in the rigor-cycle. In chapter 3, 5, 7, and 8 on the other hand we iterate the design cycle with various pre-evaluations and updates on the studied artifacts. Finally, in the relevance cycles we study the impact of our artifacts on their respective environments in chapter 4, 6, 9, and 10. The main difference between the evaluations in the design cycles and the ones conducted in the relevance cycles is the targeted results. While the design cycle evaluations focus on the usability evaluation and refinement of our artifacts, the relevance cycle evaluations focus on the artifacts' impact on the targeted environments and their limitations in a field environment. In contrast to part 1 (figure 2 (left)) which traverses both the design cycle and relevance cycle once for two artifacts, part 2 (figure 2 (right)), consecutively traverses through two design cycles before adding two consecutive relevance cycles.

1.4 OUTLINE

This thesis consists of four major parts that are introduced in the outline below. The way chapters build upon each other is additionally shown in figure 3.

The first part lays the foundation of this thesis by introducing the topics that were addressed (chapter 1), giving an overview of the fundamental concepts in nutrition science and psychology that are utilized later in the thesis, and reviewing the current state of the art in the fields concerned with this thesis' topic.

Chapter 1 provides the research area's motivation, a clear problem statement, including the research questions targeted in this thesis, the methodology used to address these questions, and the outline of this thesis.

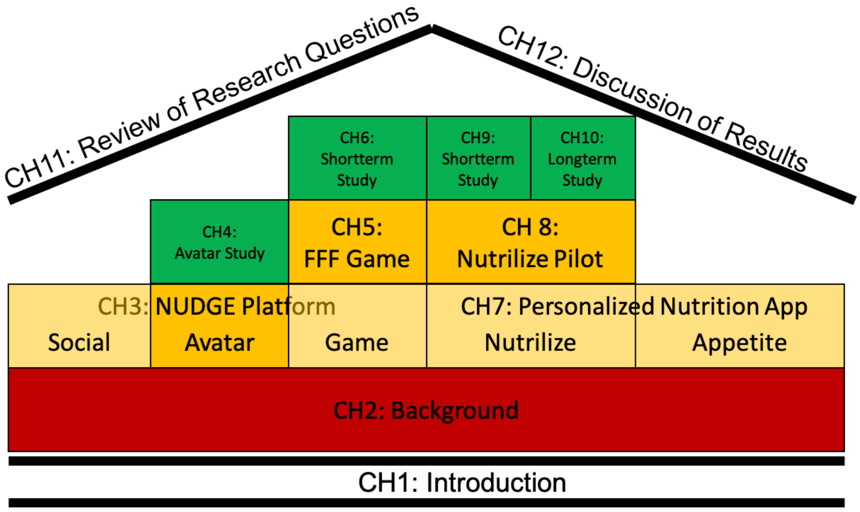


Figure 3: Building upon this introduction, we lay the fundament of this thesis with a rigor-cycle (red) in the background chapter. The chapters are split up into the two parts of this thesis (children and adults). Both parts start with a broad design cycle (lights yellow) and reiterate the parts of that design (yellow), which are eventually introduced to the field in the three relevance cycles (green). The thesis is concluded by a review of the initial research questions and a discussion of the overall results from all cycles in both parts.

Chapter 2 reviews the literature and market situation regarding the current state of the art of nutrition interventions, applications, and models.

The second part provides the research contributions towards the first case study of socio-technical systems for healthy nutrition, targeting young adults. This case is divided into five separate chapters describing the different research modules and stages.

Chapter 3 elaborates on the design feedback from focus groups on the socio-technical system *NUDGE*.

Chapter 4 discusses the results of a field user study on the avatar concepts of the *NUDGE* platform.

Chapter 5 reviews each of the design iterations and subsequent evaluations of the *Fit Food Fun* serious game.

Chapter 6 discusses the results of a field user study on the *Fit Food Fun* game.

The third part provides the research contributions towards the second case study of socio-technical systems for healthy nutrition, targeting the adult population. The second case is again divided into five separate chapters describing the different research modules and stages.

Chapter 7 reviews each of the design iterations and subsequent evaluations of the socio-technical system *Nutrilize*.

Chapter 8 elaborates on the design feedback received in the pilot study on the *Nutrilize* system.

Chapter 9 discusses the results of a short-term study on Rasch-based goal tailoring within the *Nutrilize* system.

Chapter 10 discusses the results of a long-term field study of the *Nutrilize* system.

The fourth and final part of this thesis discusses the previous chapters and summarizes their overall conclusion.

Chapter 11 summarizes the contributions of this thesis to each of the four research questions.

Chapter 12 discusses the contributions concerning their limitations and gives an outlook into future research questions.

1.5 PUBLICATIONS AND SUPERVISED THESES

Part of the ideas and figures in this thesis have appeared previously in publications I coauthored or bachelor's and master's theses I advised. A complete list of these publications is given at the beginning of the thesis, and a list of advised bachelor's and master's theses is given in the second part of the bibliography. Below I give an overview of how each chapter and its partial contents are influenced by previous publications and bachelor's and master's theses. For legibility reasons, any literal citation of own previous publications within the chapters themselves is color-coded in the same gray color as this sentence without giving a citation to the respective paper. The exact citations are listed in detail in appendix A.

Chapter 1 gives an introduction to the thesis and does thus not contain any material from previous publications or advised bachelor's and master's theses.

Chapter 2 reviews research in traditional nutrition interventions, commercial nutrition applications, and digital/automated nutrition modeling. The sections reviewing work on health recommender systems make frequent references to a review paper submitted to the digital health conference 2017, of which I am the first and main author (Schäfer et al., 2017b). The sections reviewing the challenges and open questions for nutrition modeling make frequent references to a theory-opinion-reflection paper submitted to UMAP 2017, of which I am the first and main author (Schäfer et al., 2017a).

In chapter 3 elaborates on the design concept of our serious games platform, *NUDGE*, and a focus group evaluation of this concept. The first half of the chapter is taken from a publication at ChiPlay's Positive Gaming workshop, of which I am the first and main author (Schäfer et al., 2017). Parts of the evaluation have been discussed in the master's thesis of Tobias Weiher (Weiher, 2018), which I advised. An abstract of the survey that this design is based on was already given at a nutritional congress prior to the workshop publication (Holzmann et al., 2017). A complete publication on the survey results was published at JMIR From Res (Holzmann et al., 2019a) and JMIR Serious Games (Holzmann et al., 2020). I was either the third or second author on these publications, after the nutrition medicine doctoral student and bachelor student. The survey results are only discussed shortly in this chapter.

Chapter 4 discusses the results of a study testing the motivational effect of an avatar as a design element of the *NUDGE* platform. This chapter is entirely taken from a late-breaking-results paper at UMAP 2018, of which I am the first and main author (Schäfer et al., 2018). Furthermore, the study is discussed in the master's thesis of Sebastian Pretschner (Pretscher, 2016), which I advised.

Chapter 5 reviews the design process and pre-evaluations of our designed game for the *NUDGE* platform, *Fit Food Fun*. Though this work has not been published yet, it has been discussed in multiple bachelor's and master's theses that contributed partial results to the game design. The bachelor's and master's theses have been jointly advised by me and my colleague David Plecher, with four bachelor's and master's theses being officially attributed to me (Brandl, 2017, Weber, 2018, Borchers, 2018, Di Mango, 2018) and three to my colleague (Struzek, 2015, Ziegltrum, 2017, Bao, 2018). Additionally, alternative games to the *Fit Food Fun* game were developed under the supervision of my colleague David Plecher (Rösler, 2017, Mitschenko, 2017, Soyer, 2017, Neumann, 2017, Le, 2016, Mück, 2017, Böker, 2018, Barounig et al., 2017).

Chapter 6 discusses the results of the user study on the effects of the *Fit Food Fun* game. Parts of these results concerning the nutritional viewpoint have been published as a paper in the Nutrients Journal with me as the second author (Holzmann et al., 2019b). Another paper comprising the contents of this chapter with a stronger focus on the computer science aspects of the study is in preparation. The process of the first part of the study and the preliminary evaluation have been discussed in the bachelor's thesis of Sarah DiMango (Di Mango, 2018), which I advised.

Chapter 7 reviews the design process and pre-evaluations of our designed nutrition assistance system, *Nutrilize*. An early design version has been published as research in progress at the ICIS conference in 2016 (Terzimehić et al., 2016) and discussed in the master's thesis by Ivan Petrov (Petrov, 2016), which I advised. Chapter 7 moves beyond the descriptions in this early paper (Terzimehić et al., 2016), but a few paragraphs make frequent references to the content of this publication, such as the classification of our features according to the persuasive system design framework (Oinas-Kukkonen and Harjumaa, 2009). Though the design process has not been published, it has been discussed in multiple bachelor's and master's theses I advised that contributed partial results to the systems improvement (Petrov, 2016, Wagner, 2016, Frenzel, 2017, Palm, 2017, Kienmoser, 2017, Mainz, 2017). The design of the visualizations was developed in an interdisciplinary project advised by my colleague Nadja Leipold (Moyon et al., 2017).

Chapter 8 elaborates on a pilot study testing the usage patterns and perception of the *Nutrilize* system. The study results were previously published in a workshop paper at the HealthRecSys workshop in 2018, and a few paragraphs of this chapter are closely related to the content of this paper. Although I am the third author of this paper, I contributed the system development, the study conduction, the data evaluation, and large parts of the writing of the paper (Leipold et al., 2018). An abstract of this study was already given at a nutritional congress prior to the workshop publication and reports on the same results (Madenach et al., 2017). Additionally, the initial algorithmic designs are discussed in two master's theses I advised (Hecktor, 2015, Ramirez, 2017).

Chapter 9 discusses the results of a user study on the effect of tailored goal setting within the *Nutrilize* system. This study was conducted in collaboration with the Eindhoven University of Technology and has been published as a full paper at IUI 2019, of which I am the first and main author (Schäfer and Willemsen, 2019). The chapter is entirely taken from this publication. This study's data are discussed concerning nutrition patterns by a master's thesis (Mohl, 2018) I advised whose results are not directly integrated into this chapter.

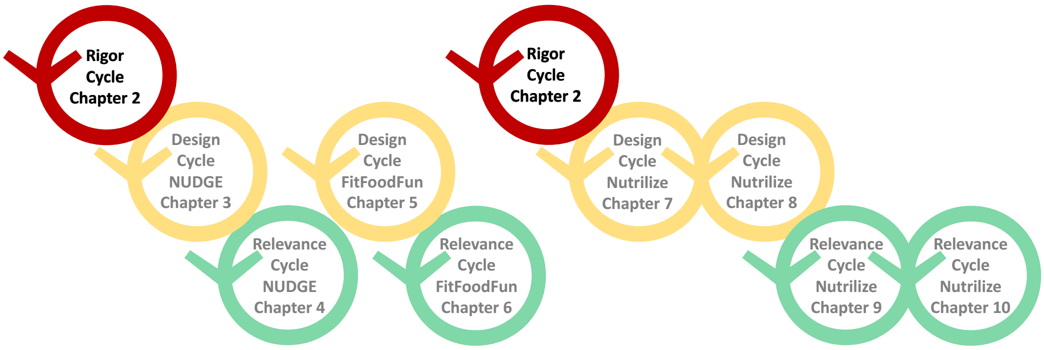
Chapter 10 discusses the results of the long-term user study done on the effects of the *Nutrilize* system. These results have not been published yet, but a paper comprising this chapter's contents is in preparation. This study's data are discussed concerning user patterns (Wieser, 2018) and diversity (Dubińska, 2018) by two bachelor's and master's theses I advised whose results are not directly integrated into this chapter. This study has furthermore been analyzed in two nutrition science bachelor's theses whose supervision I was not involved with (Kammermeier, 2018,Gutmair, 2018).

Chapter 11 and 12 give a summary of this thesis, discuss the results and limitations, and provide an outlook on future work. None of these chapters contains content from previous publications.

This chapter discussed why socio-technical systems could provide one approach to lessen the world-wide issue of unhealthy nutrition. We derived the interactions of such socio-technical systems with knowledge, motivation, behavior, and real-life context as the four main areas on which we want to focus our research. To derive how a socio-technical system can influence these areas, we aligned our research with the design science guidelines and cycles. In two parts, we design and evaluate socio-technical systems for children and adults. Both parts build on one shared rigor cycle addressing the former state of research, reviewed in the following chapter.

2

BACKGROUND



This chapter reviews state-of-the-art literature in traditional nutrition interventions, commercial nutrition applications, and digital/automated nutrition modeling. The sections reviewing work on health recommender systems make frequent references to a review paper submitted to the digital health conference 2017, of which I am the first and main author (Schäfer et al., 2017b). The sections reviewing the challenges and open questions for nutrition modeling make frequent references to a theory-opinion-reflection paper submitted to UMAP 2017, of which I am the first and main author (Schäfer et al., 2017a). All design and relevance cycles of this thesis are grounded in one extensive rigor cycle. As a methodology, we review previous work from nutrition science, psychology, and computer science, specifically regarding different system definitions, nutrition interventions, nutrition applications, nutrition modeling approaches, and health applications. Both the review of work on nutrition interventions and the review of nutrition applications are presented in chronological order to incorporate the evolution and improvement of approaches. This chapter aims to extract the common requirements that need to be fulfilled in any successful socio-technical system for healthy nutrition. More specific related work on the final concepts applied to meet these requirements during the subsequent design cycles is reviewed in the corresponding chapters.

2.1 SCOPE OF REVIEW AND DELIMITATION OF SOCIO-TECHNICAL SYSTEMS

The rigor cycle performed in this chapter looks at different aspects relevant to the design and effectiveness of systems that support healthier food choices. Our main goal is to derive requirements for our subsequent design and relevance cycles from different perspectives in previous literature. The angles we investigate are the effectiveness of traditional nutrition interventions, the feature set of commercial nutrition applications, the challenges of the system's modeling component, e.g., user modeling and automated nutrition evaluation, and finally, the system's challenges of the interface component, e.g., trust, empowerment, and persuasion.

Before going into details on each of these four angles, we first delimitate the type of systems we want to target in our research. In the literature on nutrition interventions, different definitions are distinguished. Forster et al. (Forster et al., 2015) separate systems into three different categories: online (web-based), mobile-based, and sensor-based systems. A broader distinction is given by Widmer et al. (Widmer et al., 2015), who additionally include telemedicine, email interventions, and text messaging into their definition of digital health interventions. In the papers assessed in the subsequent sections, the following types of intervention types were named: computer-based interventions (Wieland et al., 2012), mobile-based interventions (Azar et al., 2013,Carter et al., 2013,Lyzwinski, 2014,Mateo et al., 2015), online interventions (Kohl et al., 2013,Forster et al., 2015), internet-based interventions (Kohl et al., 2013, Marsaux et al., 2015, Celis-Morales et al., 2015, Forster et al., 2016, Livingstone et al., 2016), and web-based interventions (Neve et al., 2010, Kelders et al., 2012, Carter et al., 2013, Marsaux et al., 2015, Celis-Morales et al., 2015, Forster et al., 2016).

Within this thesis, we will subsume all of these systems under the term of socio-technical systems. This term originates from the work organization area where it targeted the equal consideration of human elements compared to technical factors when improving or changing an organizational system (Mumford, 2006). In its core, it describes a philosophy aiming at a humanistic approach to technological change (Mumford, 2006). Over the years, the term has expanded and was used in a variety of contexts. The common elements of all those contexts are a combination of humans and technology within some form or organizational environment targeted at reaching a goal. According to Baxter et al., (Baxter and Sommerville, 2011) modern approaches sometimes focus on social systems in their various forms, while at other times, they target only improving the technical component, but rarely both. Baxter et al. further see a strong embedding of socio-technical awareness in the field of human-computer-interaction (Baxter and Sommerville, 2011). Finally, David et al. (Davis et al., 2014) suggest in more recent work on socio-technical systems to expand the socio-technical system beyond the term "system" and "organization" to encompass larger modern challenges such as government initiatives to support environmental sustainability.

For our thesis's scope, we apply the terms of a socio-technical system by fulfilling the goal of healthy nutrition targeted by the state as an organization for its members within their social contexts by means of a technological application. The organization we are referencing is the society or state that wants to reach a healthier population. One example of an organizational step towards this goal is introducing mandatory food labels to improve customer awareness (Union, 2011). The human and social aspects we are referencing are the members of a population whose nutrition should be improved as well as their social context. Various social contexts can be considered in such a socio-technical system. A comprehensive overview of social contexts and how they can be determined is given by Groh (Groh, 2011). One example of a social context relevant to our system is the actual physical, social context during eating situations, e.g., at family or work lunch, which can influence immediate food choices. The virtual social context of social media platforms, on the other hand, affects the opinions and perceptions of people. In an even broader definition, the context of a society with its acceptance or dismissal of certain behaviors, e.g., ideal body images, shapes the individuals' goals within that society. Finally, we use the term of the socio-technical system to subsume the systems mentioned above that target a technological intervention on this network of humans, social aspects, and organizational factors.

2.2 NUTRITION INTERVENTIONS

Nutrition interventions have been conducted for a long time, leading to a multitude of trials focussing on different effecting factors or target populations. The following section analyzes the most important papers on nutrition interventions and their conclusions of effective conditions for conducting them. The first section of related work covers traditional interventions starting with a paper on the past 25 years written in 1997 and going up to the year 2016. Each paper focusses on a different aspect of the trial, such as the type and duration of intervention. The second section specializes in related work on interventions for children. This type of intervention is often limited to specific conditions, e.g., school-based interventions, or more differentiated goals, e.g., increase of fruit consumption, than in adult trials. The third section focuses on the first internet-based interventions starting with early work from 2010 and covering different types of conveying media and provided content. The final section covers the idea of personalized nutrition and the results of the Food4Me project on this topic.

2.2.1 *Traditional Nutrition Interventions*

One of the earliest papers (Miller et al., 1997) was written in 1997 on therapeutic interventions during the past 25 years with the goal of weight loss. When comparing 493 different diet or diet and exercise interventions, they note that the participant group is very limited to middle-aged, slightly overweight people. The authors further note that most studies are of short duration around 15 weeks and produce around 11 kg of weight loss. Furthermore, exercise as an addition to the diet intervention increases the maintained weight loss at a one year follow up to approximately 8.6 kg instead of 6.6 kg.

More recent papers reported on this subject show similar results. For example, Franz et al. (Franz et al., 2007) assessed 80 studies with at least one year follow up in 2007. The authors conclude that different dietary interventions can lead to a weight loss of 5 to 8.5 kg. However, they note that this loss plateaus after approximately six months and can only be partially maintained (3 to 6 kg) with continued professional support.

The meta-regression of Michie et al. (Michie et al., 2009) not only compares the effects of weight/loss trials but investigates the underlying techniques of healthy eating and physical activity interventions. The authors classify interventions according to five intervention techniques from control theory (Carver and Scheier, 1982) (i.e., prompt goal setting, specify goals concerning contextualized actions, self-monitoring of behavior, feedback on performance, and review of previously-set goals). The authors combine 122 evaluations and show that self-monitoring is the most promising technique to be included in an intervention. The authors further show that interventions combining self-monitoring with any of the other four techniques are significantly more effective than interventions without these techniques. Due to a lack of available studies, they could not conduct a comparison of studies that include all five techniques.

While Michie et al. compare techniques across both diet and physical activity interventions, the paper by Wu et al. (Wu et al., 2009) additionally focusses on the distinction between trials that focus on diet only, and trials combining exercise with diet interventions. The authors assessed 18 randomized trials with a long-term intervention time and noted that the combination of diet and exercise produced stronger long-term effects on weight than diet-only interventions. The authors further show that the duration of the intervention can increase long-term weight loss at a modest rate of 1.64 kg on average. Survivor's bias can partially explain this success due to a large dropout in long-term studies. The positive effect of adding exercise interventions is especially effective in the long-term, e.g., 2-year, interventions. The authors thus suggest a prolonged active intervention in person or via phone and email.

This argument of extended care is further investigated by a paper by Ross et al. (Ross Middleton et al., 2012). The authors conducted a meta-analysis of 11 studies and show that adding extended care has a significant effect on long-term weight regain. Their analyses predict that the effect would lead to 3.2 additional kilograms or weight loss over 17.6 months post-intervention.

In addition to the duration of interventions, the paper of Kirk et al. (Kirk et al., 2012) investigates the effectiveness of different types of interventions. The authors show that multi-component interventions are more effective than dietary manipulations or weight management interventions alone, confirming most clinical practice guidelines. The authors further note that interventions should provide long-term support from trained health professionals and tailored towards the individual. Finally, they encourage web-based technologies to support traditional care models.

Similarly, the paper by Johns et al. (Johns et al., 2014) shows that Behavioral Weight Management Programs (BWMPs)s are more effective than single-component programs. The authors compared eight Randomized Controlled Trials (RCTs) on overweight and obese adults with BWMPs, diet-only, or physical activity-only interventions and a follow-up of at least 12 months. While there was no significant difference between BWMPs and diet-only at 3 to 6 months, they did observe a difference in favor of BWMPs after 12 months. The comparison to physical-activity-only interventions was in favor of BWMPs at both 3-6 months and 12 months.

Hartmann-Boyce et al. (Hartmann-Boyce et al., 2014) also studied the effectiveness of BWMPs by comparing 37 RCTs of multicomponent BWMPs. In contrast to other reports, their analysis showed no evidence for the influence of supervised physical activity sessions, more frequent contact, or in-person contact, at a 12-months follow-up. However, the authors did find an effect on weight loss for calorie counting, contact with a dietician, and use of behavior change techniques, especially social comparison. The authors further expect undetected effects due to apparently similar program descriptions with substantially different outcomes.

Finally, a paper by Lemstra et al. (Lemstra et al., 2016) analyzed adherence in 27 weight loss interventions. The authors derive an overall adherence rate of 60.5%. The factors that support adherence, based on their work, are supervised attendance programs and social support. The authors further detect a higher adherence to dietary-only interventions compared to exercise-only programs.

In summary, traditional interventions are effective for weight loss. Their effectiveness can be improved by including self-monitoring and other control theory techniques or by combining different aspects of weight loss, such as diet and physical activity. The long-term regain of weight can be reduced by prolonged intervention duration and extended care, e.g., via the web. However, such extended care might also result in decreasing adherence, which could be counteracted by supervision and social support. All of the above work focuses on adults. Insights into interventions for children are reviewed in the following sections.

2.2.2 *Children Nutrition Interventions*

One special subclass of nutrition interventions surveyed separately is work regarding children. In 2007 a meta-analysis on lifestyle interventions for children was conducted by Wifley et al. (Wilfley et al., 2007). The authors compare fourteen trials that had a no-treatment or education-only control. The authors conclude that lifestyle interventions can have positive effects on pediatric overweight, and they also see persistent effects at follow-up in a part of the trials. However, they could not identify moderators such as the type and duration of the trials indicating the success of interventions. The authors further note limitations in the target group, since most trials focus on children of 6-13 years.

A similar focus is apparent in a paper by Kitzmann et al. (Kitzmann et al., 2010) in 2010. The compare results of lifestyle interventions for overweight youth and again observe a focus on 6-12-year-old participants in half of their selected studies and only four studies focusing on adolescents (13 and older). In their results, they show positive effects of lifestyle interventions, even for a relatively short duration. The authors further identify parent involvement as a critical factor for long-term success and note that many care providers are yet unprepared to deliver lifestyle interventions, requiring a shift in thinking to provide for an increasing number of overweight patients.

One solution to reduce the burden of primary care facilitators are school-based interventions for weight loss. The work of Lavelle et al. (Lavelle et al., 2012) considered 43 studies with 11 focusing only on physical activity, three focusing only on education, and 29 on improved nutrition and combined interventions. The authors conclude that physical activity, or combinations of physical activity and diet interventions, can reduce Body-Mass-Index (BMI) in overweight and normal-weight children. The authors suggest further studies on gender differences and identifying more differentiated ideal intervention types.

Another paper on school-based interventions by Evans et al. (Evans et al., 2012) focusses on fruit and vegetable consumption instead of weight loss. The note that most programs only succeed in increasing fruit intake and less in increasing vegetable intake. Additionally, the exclusion of fruit juice from total consumption measures reduced reported baseline and follow-up measures. Multi-component studies involving general dietary changes for the whole family were more effective, but also more diverse, leading to issues with replicability. Single-component programs, such as the free distribution of fruit and vegetables, were less effective but easy to implement on a large scale.

A different paper focussing on fruit and vegetable intake includes a differentiation between computer-based and multi-component interventions. While multi-component interventions achieved best results according to Evans et al. (Evans et al., 2012), the work by Delgado-Noguera et al. (Delgado-Noguera et al., 2011) shows that computer-based interventions are even more effective than multi-component interventions in the 19 cluster studies they included. Although they indicate the need for further research on this topic, they suggest computer-based interventions as effective and cheap alternatives to traditional interventions for primary schools.

The work of Ho et al. (Ho et al., 2013) focuses not only on weight loss but also on metabolic outcomes. The authors compare 15 diet and diet plus exercise interventions for overweight and obese children. While both intervention types resulted in weight loss, they show different metabolic effects. Adding exercise reduced metabolic risks, particularly HDL-C and fasting insulin levels. The authors suggest that further studies should include longer follow-ups and better strategies for improving compliance and focus on long-term sustainability.

In summary, nutrition interventions for children are effective even for short durations. Positive influence factors are interventions combining nutrition plus exercise and parental involvement. School-based interventions and computer-based interventions can help with the scalability of treatments. Open issues are adherence, long-term follow-ups, and lack of consistent data on all age groups and intervention types.

2.2.3 *Internet Based Nutrition Interventions*

One way to improve the long-term effectiveness of interventions suggested for both adults and children is extended care (Meister et al., 2016). One suitable way to provide extended care is via digital media, such as web-based interventions, text messages, and mobile applications. However, as noted in the related work above, these interventions have their own challenges, particularly with adherence. The following section reviews work focused on such digital interventions.

The first paper by Neve et al. (Neve et al., 2010) in 2010 is based on an extensive timeframe from 1995 to 2008 and thus covers the earliest approaches to web-based interventions for weight loss or maintenance. The authors include a total of 18 studies on adults with 13 focusing on weight loss and five on weight maintenance. It was not possible to determine the effectiveness of web-based interventions due to the high heterogeneity of the studies. The authors note that higher use of web-based interventions may lead to positive weight change, but the type of features improving or reducing this effect could not be determined. The authors suggest that future trials should compare web-based with traditional delivery methods for the same well-designed lifestyle interventions. The authors further note that future studies need to determine the type and dosage of useful web-based components as well as the effects of mediating variables such as engagement and retention rate.

Two years later, a paper by Wieland et al. (Wieland et al., 2012) compared the effectiveness of computer-based interventions for weight loss and maintenance to in-person interventions. The authors included 14 weight loss and four weight maintenance studies. Both in-person treatment and computer-based treatment lead to higher weight loss and weight maintenance than minimal intervention control groups at six months. The in-person treatment was more successful than the computer-based intervention in both cases. An attempt to compare the cost between both types of intervention leads to no conclusive results due to differences in the target group and conduction time. The authors conclude that while less effective than in-person treatment, computer-based interventions are an effective tool for weight loss and weight maintenance.

The paper by Kelders et al. (Kelders et al., 2012) in 2012 addresses the mentioned issue of measuring and influencing adherence in web-based interventions. The authors conduct an extensive comparison of 83 interventions and measure which aspects of system design consistently influence adherence. From their set of articles, they conclude that a typical web-based intervention is planned for once a week usage, lasts for ten weeks, and includes interactions with the system, a counselor, and peers. Most interventions already include persuasive technology elements and have a dropout of about 50%. The authors identify primary task support as the most commonly employed persuasive element. Dialogue or social support are used less frequently. Different target areas of the intervention widely differ in parameters such as setup, frequency, the intention of interactions, duration, and adherence. The final regression model they extracted could explain 55% of the variance in the adherence to these interventions. This model shows that RCTs have higher adherence than observational studies. The model also shows that increased interactions with a counselor, more frequent usage or updates, and more extensive dialogue support, have a positive effect on adherence. Despite differences between health areas, these technology choices were a stronger predictor for adherence across all studies than the target area itself. The authors strongly encourage planning and designing for adherence for any web-based intervention. The authors note that even studies that claimed to plan for adherence do so in a non-systematic way or leave this task to the human part of the intervention. Furthermore, studies that did design the system for adherence often did not do so without considering theoretical foundations. The authors propose the Persuasive System Design (PSD) model (Oinas-Kukkonen and Harjumaa, 2009) might be an adequate guideline to improve and streamline the process of designing for adherence in web-based health interventions.

A very critical work was published by Kohl et al. (Kohl et al., 2013) in 2013. Their analysis of 41 studies published between 2005 and 2012 shows that most overall effects measured by the interventions are small and not sustainable. The authors additionally criticize that participants across different studies are mostly female, highly educated, white, and living in high-income countries. The authors further note that the actual use of offered interventions is low across all behavior domains, and the determinants of effectiveness can not be attributed to isolated elements yet. The authors propose more research on effective factors instead of effective interventions, higher diversification of participants, and a stronger focus on these effects' long-term sustainability. Finally, they suggest possible benefits of conducting online interventions regarding these issues. Online interventions could potentially provide a broad reach in recruitment. The authors could give the possibility of establishing extensive user profiles for tailored advice. Further, the addition of more granular data collection, such as log-ins and page views, could help in disentangling the effective components of health interventions. Combined with extensive user profiles, this could also tackle the question of effectiveness for specific subgroups.

The work by Lyzwinski et al. (Lyzwinski, 2014) in 2014 focusses more specifically on interventions for weight loss with mobile devices instead of general issues of web-based or computer-based interventions for health. The authors want to determine mobile interventions' effects compared to both control groups and non-mobile weight loss interventions. Their paper concludes that weight loss interventions by mobile device medium induce a medium effect for weight loss. Both comparison of pre- and post-intervention weight as well as comparisons between intervention and control arm, both no treatment and non-mobile treatment, were in favor of mobile device interventions. The authors consider publication bias to be a mediating factor in these results but conclude that the results would favor mobile device treatment even with smaller effect sizes. The authors further found that mobile devices induce reductions in waist circumference, BMI, and body fat percentage compared to both baseline and control arm. Finally, they show positive behavior change, e.g., in the form of increased physical activity and diet, for mobile device interventions. Improvements in diet were found concerning the intake of fruit and vegetables, sugar intake, and energy-dense food intake. Besides the effectiveness of mobile device interventions, they also assessed commonly applied psychological theories and behavior change techniques. The most common theories identified were: Social Cognitive Theory, Implementation Intentions Theory, Elaboration Likelihood Theory, Goal Theory, and Control Theory. The applied behavior change techniques ordered from most to least frequent were: goal-setting, self-monitoring, feedback, prompting practice, providing general encouragement, providing social support, prompting barrier identification, providing instruction, providing opportunities for social comparison, relapse prevention, and stress management. These theories' use resulted in the improvement of the targeted aspects such as user control, positive affect, elaboration, and intentions. The authors conclude that mobile weight loss interventions have a high potential for stimulating behavior change. However, they caution that such improved interventions with longer duration and improved methodology are needed to demonstrate meaningful and sustained weight loss.

In 2015 Mateo et al. (Mateo et al., 2015) analyzed mobile phone apps targeting weight loss and physical activity. Their analysis of 12 articles on mobile phone app interventions related to weight shows significant changes in weight or BMI compared to control groups and non-significant differences in physical activity. The authors explicitly exclude interventions based on only text messaging. The authors summarize the advantages of mobile phone applications over other mobile interventions, namely portability and 24h access, long-term reinforcement, and automatic tracking of physical activity. Despite the positive outcome of their analysis, the authors note challenges when using mobile phone apps. The authors discuss attrition as a common problem in weight-related interventions leading to a survivor's bias in the published results. The authors further establish adherence as a severe problem, with many participants not using the application anymore after only one month and conclude that this issue might shift the measure of effective mobile apps towards those with long-term adherence.

Schoeppe et al. (Schoeppe et al., 2016) extend the analysis of single component mobile app interventions towards combinations of interventions. Their analysis of 27 studies shows that more studies show significant between-group improvements than within-group improvements. The authors further note that more multi-component interventions showed greater between-group improvements than single-component interventions. Finally, three of the eleven studies reporting usage statistics indicate that higher app usage is associated with improved health outcomes.

In summary, initial work on web-based and computer-based interventions were quite critical and detected issues with smaller effects, higher costs, and higher dropout than in-person treatments. The authors further show a need for systematic design and component-based analysis of such interventions. With an increasing inclusion of psychological theories and behavior change components, as well as a shift towards mobile technology, more papers report positive effects compared to non-mobile interventions. All surveyed papers emphasize a need for further research to prove robust and replicable long-term effects of mobile interventions and a need for the systematic and regulated design of mobile applications.

2.2.4 *Personalized Nutrition Interventions*

Most of the previously assessed papers covered traditional interventions in either human delivered or digitally delivered content. One trend in more recent interventions is personalized nutrition. The Food4Me project did an extensive study tackling this field. We subsequently review papers focussing on the design, conduction, and results from the Food4Me study.

In 2015, Forster et al. (Forster et al., 2015) published a paper on the utility of different dietary assessment methods regarding personalized nutrition. The accurate and complete assessment of dietary behavior is an essential precondition to providing personalized nutrition feedback. The authors compare traditional methods such as food diaries, dietary recalls, and FFQs with new technologies, such as online (web-based) methods, mobile methods, and sensor technologies. Dietary intake data is necessary for many types of nutritional interventions and especially for the delivery of personalized dietary advice. Compared to traditional assessment methods, new technologies have the advantage of possible automatic processing of data and of being able to provide personalized dietary feedback. These technologies further reduce the burden for both users and researchers. However, such technologies are at varying stages of development and validation. Several studies have shown how new techniques, predominantly online methods, providing tailored advice can lead to positive dietary changes. There is a further need for examining the validity of mobile methods and sensor technologies. Additionally, varying frequency, sensitivity, and type of feedback lead to differences in effects. The authors conclude that comparison across studies is necessary to establish the utility of such technology-based dietary assessment tools for personalized dietary feedback.

Celis-Morales et al. (Celis-Morales et al., 2015) justify the design of the Food4Me study and discuss the characteristics of their participants at baseline. This study aimed to conduct a web-based study on personalized nutrition in multiple study-centers across Europe. After an initial screening, 1607 of the interested 5562 participants were invited to participate in the study. The duration of the intervention was six months. Participants were grouped into four levels of advice: 1) a control group receiving conventional advice 2) a group receiving personal advice based on dietary intake 3) a group receiving personal advice based on dietary intake and phenotype 4) a group receiving personal advice based on dietary intake, phenotype, and genotype. The mean age was 39.8 years, with 60.9% female participants and 96.7% white-European background. The mean BMI was 25.5, with 44.8% of participants being overweight or obese.

Marsaux et al. published the first results of the Food4Me study (Marsaux et al., 2015), focusing on the effect on physical activity. Physical activity was measured for six months using an accelerometer and Baecke questionnaires after three and six months. The authors observe a greater improvement in self-reported physical activity and physical activity during leisure time in personalized groups. This effect is even stronger for participants who were advised to increase physical activity. However, there were no significant differences between groups, when analyzing the accelerometer data, and no significant effects for adding phenotypic and genotypic information to the tailored feedback. The authors conclude that objective physical activity measures are essential to any personalized intervention study.

The report by Forster et al. (Forster et al., 2016) focusses on results related to the dietary feedback system used in the Food4Me study. The dietary feedback system developed in Food4Me consists of multiple components. An online FFQ assesses nutritional intake. Each nutrient's intake is classified into one of five classes: very low, low, optimal, high, and very high intake. Additionally, all nutrients were classified into one of three groups and ranked by priority. Of each group, the least optimal nutrient with the highest-ranking priority is chosen as a goal and given a particular focus in the report. Decision trees automatically select fitting feedback messages for the final report. During the intervention, the automated system was emulated manually by researches to provide the final report. The average agreement between manual and automated results ins selecting the three nutrient-related goals was 92% for the first goal, 87% for the second goal, and 63% for the third goal. The authors conclude that the agreement supports the future development of an automated feedback system across multiple counties. The authors further note the potential of scalable and cost-effective interventions using such a system. Finally, the system assessed in this paper is targeting the usual intake measured with FFQs. Future research should address the actual intake at purchase or consumption time.

The results of personalized advice on dietary behavior (Food4Me Study, 2016a) is evaluated using the Mediterranean diet (MedDiet) (Davis et al., 2015). Already at baseline, participants with higher MedDiet scores showed lower BMI and higher physical activity levels. The comparison after six months of intervention shows higher scores according to the MedDiet for personalized advice than for the control arm. The phenotypic and genotypic groups showed no significant difference to the group with personalized feedback based on dietary intake. Overall the DNA-based advice resulted in the largest difference in MedDiet scores at month six. Although personalization effects are significant in total, the average improvement of the MedDiet score indicates only modest health benefits. The authors conclude that personalized advice is beneficial, but needs to be improved to provide stronger and more sustainable effects. The authors further note that the internet-based delivery of this advice offers a scalable and cost-effective solution.

Another evaluation of effects on a healthy diet during the Food4Me study (Celis-Morales et al., 2016) focuses on health-related behavior changes. The authors show that participants receiving personalized feedback consumed less red meat, less salt, less saturated fat, more folate, and had higher Healthy Eating Index (HEI) scores at month six than the control arm. There was no evidence for additional benefits when including phenotypic and genotypic information. The authors conclude that personalized advice via internet-delivered interventions is more effective than the conventional "one size fits all" approach, especially when including personal eating patterns. The authors also emphasize that internet-based interventions show promising benefits regarding recruiting and retention of participants.

The third evaluation of dietary changes during the Food4Me study (Livingstone et al., 2016) focusses on changes in the HEI for different clusters of participants. To distinguish different types of participants, they were clustered by their adherence to European dietary recommendations. The resulting four clusters are split into participants meeting all recommendations except for red meat (C1), individuals meeting two recommendations (C2), and individuals meeting only one recommendation (C3 and C4). The group with the poorest diet (C4) also had more smokers than C1 and wanted to lose weight more than in C1. Individuals in this group who received personalized advice reported greater improvements in their HEI than individuals in C1 and C3. The same clusters showed no difference in results when treated with conventional non-personalized advice. The authors conclude that the efficacy of personalized advice is highest for participants with poor diets. The authors further note that a coherent clustering of participants may be beneficial for the design of new health promotion actions.

In summary, Food4Me shows the first promising effects of personalized dietary advice systems. The automated feedback on dietary intake measures with FFQs shows good correspondence with manual recommendations, offering positive feedback for automated dietary advice. Both self-reported physical activity and diet showed greater improvement in personalized groups. Especially participants with low initial adherence to dietary guidelines could profit from personalized advice. The addition of phenotypic and genotypic data to personalization based on dietary intake provided no significant benefits.

2.2.5 *Summary and Conclusion*

While traditional methods for personalized nutrition support are shown to be effective by many studies, they are not efficient or scalable concerning the resources required to provide them. In contrast, internet-based nutrition support is shown to be scalable and shows similar effectiveness to traditional interventions. Commercial nutrition applications have become widely available on the market, but show drawbacks which are reviewed in the following section. Additionally, both commercial and research applications for nutrition support struggle with high dropout rates. On the other hand, personalized nutrition support promises more effective health improvements than population-based interventions and is dependent on internet-based solutions. A special case is the intervention design for children. In contrast to adult interventions, factors such as parental involvement are essential for effectiveness. Furthermore, many commercial applications are targeted at adults and weight loss. The case of children (part II) is thus handled separately from the case of adults (part III).

2.3 NUTRITION APPLICATIONS

Table 1: An overview of the mobile applications that were assessed in at least two different papers of this chapter. The rows are sorted by frequency.

Application Name	(Azar et al., 2013)	(West et al., 2013)	(Chen et al., 2015b)	(Rohde et al., 2017)	(Holzmann et al., 2017)	(Franco et al., 2016)	(Schneider, 2015)	(Zhang et al., 2019)	(Fallaize et al., 2019)
MyFitnessPal	x		x			x	x	x	x
Lose It!	x	x				x		x	x
Noom			x			x	x		x
FatSecret						x	x	x	x
YAZIO				x			x	x	
Lifesum						x	x	x	
FDDB					x		x		
Samsung Health						x			x
Calories!							x	x	
Lose Weight Without Dieting						x	x		
My Diet Coach			x			x			
MyPlate			x					x	

Mobile nutrition and fitness applications are already frequent in both the Google Play Store for Android and the iTunes App Store for iOS. To determine the state of the art in commercial applications, we surveyed different papers regarding these types of applications. There are three early works conducted by Azar in 2012 (Azar et al., 2013), West in 2013 (West et al., 2013), and Chen in 2015 (Chen et al., 2015b). In our design science cycle, we surveyed popular apps (see also (Schneider, 2015)). Furthermore, three paper were written in parallel to the early phase of the *enable* project by, Rhode (Rohde et al., 2017), Holzmann (Holzmann et al., 2017) and Franco (Franco et al., 2016) in 2016. Finally, five papers (Flaherty et al., 2018, Fuchs et al., 2018, Mauch et al., 2018, Zhang et al., 2019, Fallaize et al., 2019) were written after the implementation of our prototypes, but are included as confirmation of our findings on critical gaps in commercial applications. In addition to these analyses, we took a closer look at the four apps that were evaluated in more than two paper to get an impression of their feature range: MyFitnessPal (LLC, 2019a)(6 mentions), Lose It (LLC, 2019c)(5 mentions), FatSecret (LLC, 2019b)(4 mentions), Noom (LLC, 2019d)(4 mentions). An overview of the most frequent mobile applications assessed in the different papers is given in table 1.

2.3.1 *Early Work*

One of the earliest papers by Azar et al. (Azar et al., 2013) in 2015, analyzes ten popular apps regarding their integration of behavior change theories and persuasiveness. Their selection refers to the top two samples of each of the five categories "diet tracking", "healthy cooking", "weight/anthropometric tracking", "grocery decision making", and "restaurant decision making", derived from an initial sample of 200 mobile applications. The authors conclude that app developers focus primarily on their applications' UI and technical aspects instead of possible underlying theories. In cases that include behavioral theories, they were based on basic and traditional constructs. The authors suggest that these apps could become more effective when adding other components, such as persuasive technology. Finally, they criticize that none of the applications underwent any formal evaluation regarding their effectiveness. On the other hand, they admit that long-time adherence due to positive interface aspects might, in the end, be as crucial to the effectiveness as advanced behavioral strategies. West et al. (West et al., 2013) went one step further and did a structured rating of health behavior theory constructs within the user interaction dimensions of 58 mobile nutrition applications. The most common construct was general information, shorty followed by knowledge and cognitive-based strategies. On the lower end of the scale are behavioral and emotion-focused approaches. The authors especially criticize that only very few apps included features such as assessment, feedback, and individually tailored assistance. In 2015 Chen et al. (Chen et al., 2015b) took a different perspective by analyzing 28 applications for their scientific accurateness and their impact on weight loss in RCTs. The authors selected different nutrition trackers from the top applications in both Google and Apple app stores. Overall, they conclude that the apps do not meet their quality expectancy regarding scientific coverage and weight-related information accuracy. The authors also criticize the relative absence of Behavioral Change Techniques (BCTS) in the sample of applications they assessed. Concerning the effectiveness of applications, they further conclude suboptimal quality. The authors base this conclusion on the fact that studies of MyFitnessPal (Laing et al., 2014) or Lose It! (Allen et al., 2013) result in weight loss that is not statistically significant compared to the researcher-developed app My Meal Mate (MMM), which demonstrated significant weight reduction (Carter et al., 2013).

2.3.2 *Pre-Study Work*

As part of the rigor cycle, we further conducted our assessment of 22 applications, which focused on the range of features and functionalities included in the most popular nutrition applications (see also (Schneider, 2015)). The survey categorized all applications into six categories: recipe applications (e.g. eatsmarter), quizzes (e.g. NutritionQuiz), calculators (e.g. Simple BMI), information systems (e.g. Codecheck), diaries (e.g. MyFitnessPal), and restaurant applications (e.g. GastroGuide). We aim at combining all relevant features into one application, providing barcode information on nutrients, recipe information on nutrients, automatic calculation of user-profiles (e.g., BMI), and a personal nutrition diary. Furthermore, the idea of nutrition quizzes is relevant for younger audiences. As the previous papers showed, any implementation of these features should put great emphasis on both the scientific accuracy of the provided content and the application of behavior change theories. Further work that influenced design decisions at later stages in this thesis was conducted in 2016 by Rhode (Rohde et al., 2017), Holzmann (Holzmann et al., 2017) and Franco (Franco et al., 2016). Rhode et al. (Rohde et al., 2017) show from a qualitative assessment of the feedback from 17 younger adults on three commercial applications that nutrition applications need to be reliable and transparent concerning their features, easy to use concerning their design, and provide guidance, motivation, and empowerment to achieve long term adherence. Holzmann et al. (Holzmann et al., 2017) analyzed three apps for their accuracy compared to the BLS gold standard and conclude that the high divergence identifies these applications as an unreliable information source which should only be used for general orientation regarding the nutritional values of foods. Franco et al. (Franco et al., 2016) analyzed 13 applications from a set the UK's of most popular apps in both google play store and apple store and identify a significant opportunity for improvement in the form of personalized feedback, diet plans, and nutrition education.

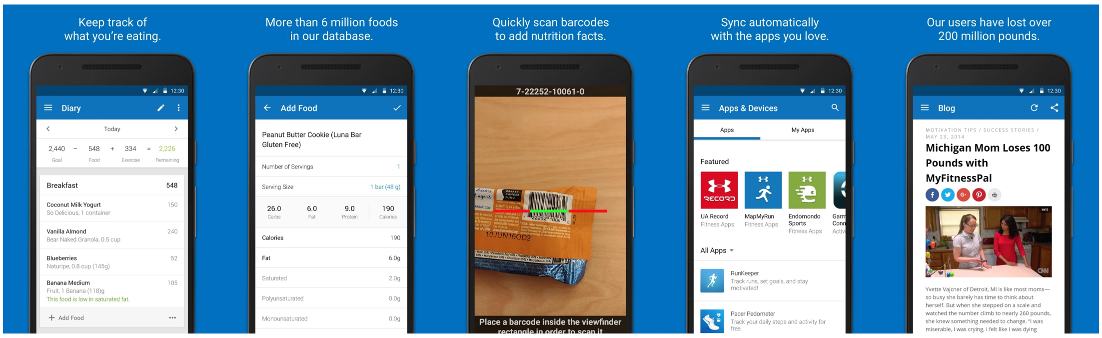
2.3.3 *Post-Study Work*

After implementing our applications, other work was published that confirmed how many of the previous conclusions are still relevant and unsolved at the time of our evaluation studies. In 2017 Flaherty et al. (Flaherty et al., 2018) did an in-depth analysis of eleven applications and determined that while the quality of nutrient information was generally good, four of the eleven applications still provided inadequate nutrient information. The authors further support the previous detection of missing customizable content and a lack of behavioral change techniques. Fuchs et al. (Flaherty et al., 2018) made a comparison of 27 popular nutrition tracking apps with a specific focus on the technology used for tracking. The authors determine that while more automated tracking is diffusing into applications as semi-automated data collection techniques, fully automated techniques remain nascent in commercial applications. Mauch et al. (Mauch et al., 2018) focused their work on 51 popular apps on the Mars score (Stoyanov et al., 2015) and feature support regarding families. The authors suggest that families would benefit greatly from applications focusing on meal planning if these applications provided personalization features, input automation, and engagement strategies. In 2019 Fallaize et al. (Fallaize et al., 2019) compared the results of nutritional intake tracking between 5 different apps. The authors conclude that the resulting macro-nutrient intake between identically inserted food items is often comparable, while the micro-nutrients between the same items are often inconsistent and less reliable. Zhang et al. (Zhang et al., 2019) further analyzed 12 apps for the nutritional representation of their recipe data. The authors similarly conclude that since micro-nutrients are vulnerable to food processing, they are often not accurately represented in the recipes' nutritional data within these applications.

2.3.4 *Feature Analysis*

To gather the positive aspects and must-haves of commercial applications, we did a feature analysis of the most commonly represented applications. There are 4 apps that are evaluated in more than 2 of the above mentioned works that are exemplified here to get an impression of their feature range: MyFitnessPal (LLC, 2019a)(6 mentions), Lose It (LLC, 2019c)(5 mentions), FatSecret (LLC, 2019b)(4 mentions), Noom (LLC, 2019d)(4 mentions). An overview of the most frequent mobile applications assessed in the different papers is given in table 1.

2.3.4.1 *MyFitnessPal*



(a) The Food Diary allows tracking of daily dietary intake.

(b) The Nutrition Database offers nutritional information of food.

(c) The Barcode Scanner allows fast and easy tracking of groceries.

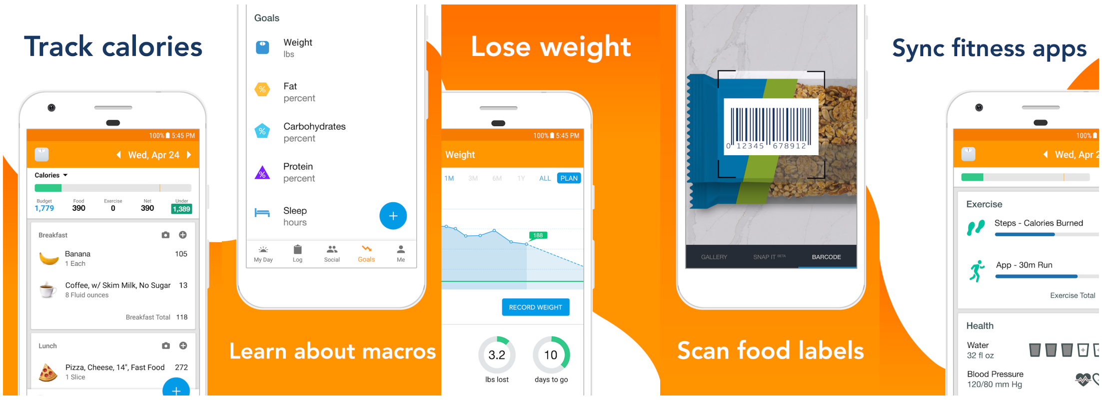
(d) The Activity Tracking allows input from various exercise apps.

(e) The Social Media blog provides motivating stories and tips.

Figure 4: Main screens of MyFitnessPal (LLC, 2019a)

The MyFitnessPal app focuses on easy-to-use tracking of food intake and its corresponding nutrients using a large food database (11+ million foods) and shortcuts such as barcode scanning (4+ million barcodes), user-generated recipes, and restaurant menus. For tracking of exercise and fitness, the application offers many interfaces to 50+ popular apps and devices. Additionally, the application provides 350+ exercises and workouts. MyFitnessPal relies on its large user base to enter new barcodes, food items, recipes, and fitness exercises. The application provides information on consumed/burned calories, water, and macro- and micro-nutrients. You can see information about these variables on either single food items or your daily tracked intake. Concerning behavior change support, MyFitnessPal provides a personal goal setting feature for any of the tracked variables. For example, you can set the goal to lose 1 pound each week or to eat at least 160g of protein each day. For the calorie tracking, the application even gives you daily feedback such as "if you continue like today, you will reach this weight in 4 weeks". Progress on weight or other nutrients is visualized in graphs over time. Additionally, photographs of the user can be uploaded to track physical changes. The application further offers exchange on news, personal progress, and tips on a social platform. Here every member can share stories, but also the company produces motivational interviews or helpful articles for learning about nutrition. This exchange can either happen in the overall community or between friends in the network. Some exemplary features are displayed in figure 4.

2.3.4.2 *Lose It*



(a) The Food Diary focuses on the calories consumed with each item.

(b) The Goal Setting allows tracking progress on different formalized goals.

(c) The Weight Tracking visualizes developments in daily body weight.

(d) The Barcode Scanner allows fast and easy tracking of groceries.

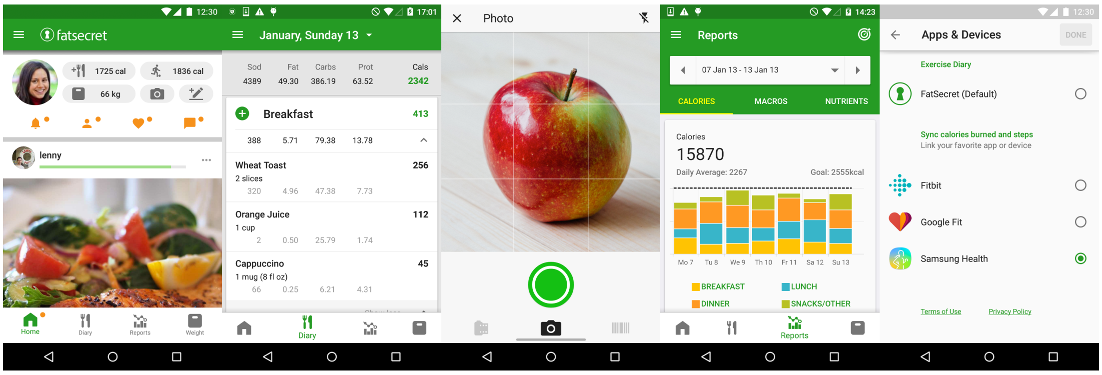
(e) The Activity Tracking focuses on calories burned during exercise.

Figure 5: Main screens of Lose It (LLC, 2019c)

The Lose It app supports similar features to MyFitnessPal, such as a food diary, nutrient feedback, goal progress tracking, and integration of fitness apps. Users' critical feedback is that Lose It supports fewer fitness apps than MyFitnessPal and sometimes is not as accurate in the calorie information provided. The application's three features beyond the MyFitnessPal app are the "Snap It" features for tracking food by taking a picture, a meal planner, and educational features, e.g., on portion estimation. While the photo recognition is one of the great additional features, some users criticize its usability, since it only recognized, e.g., "ice cream" and the brand and weight still have to be entered manually. As the social motivation feature, Lose It provides challenges against friends or the public, e.g., eat five fruits today. Important features are displayed in figure 5.

2.3.4.3 *FatSecret*

The FatSecret app also provides a food diary based on its extensive food database, including water intake tracking, barcode scanning, and picture-based tracking. The application further provides an exercise diary based on external fitness applications. To track the user's progress, FatSecret offers a diet calendar, a weight tracker, and



(a) The Photo Diary provides a photographic dietary tracking system.

(b) The Food Diary lists consumed nutrients for each food item.

(c) The Food Recognition provides a shortcut to track one's diet easily.

(d) The Data Visualization gives a visual summary of past intake.

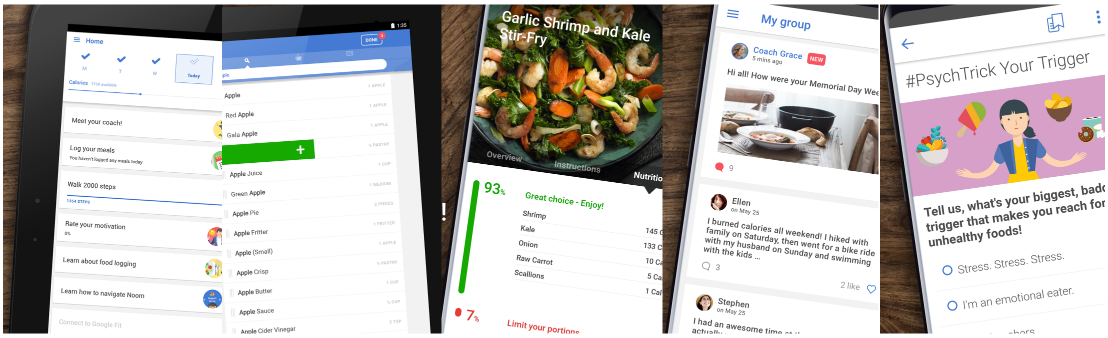
(e) The Activity Tracking connects to physical activity apps.

Figure 6: Main screens of FatSecret (LLC, 2019b)

a photo album. The application gives feedback on consumed or burned calories and nutrient intake in the form of a calendar. Similar to LoseIt, it provides a picture-based food tracking with similar drawbacks in usability. Beyond the LoseIt application, FatSecret offers a photo album for your tracked meals. The application offers to share your progress either to the community or to a professional. Finally, FatSecret provides reminders and notifications based on their meal planning tool. Some exemplary features are displayed in figure 6.

2.3.4.4 *Noom*

The Noom application has a slightly different focus than the previous apps. While providing similar food and exercise tracking functionalities, Noom emphasizes the motivational aspects of behavior change. For example, the application offers a personalized coach that tracks progress and gives feedback based on the user's goals and their preference for intervention. This coach is a real person such as a dietician or personal trainer and checks in on the progress once a week. Instead of just giving feedback on the daily intake or providing automated diet plans, the system provides feedback on small changes by color-coding previously consumed food items and slightly shifting their intake amount. Noom also includes information on psychological tricks to help the users overcome bad habits. Their articles are targeted at empowering users to detect and overcome their weaknesses instead of following a structured plan. Additionally, social support groups are matched to you after registration, where you can share experiences with similar customers. In addition to offering meal planning tools, like Lose It, Noom provides a workout planning tool. Some exemplary features are displayed in figure 7.



(a) Personal Coaching provides a list of tips and tasks to the user.

(b) The Food Diary allows tracking of daily dietary intake.

(c) The Recipe Database provides personalized portion sizes.

(d) The Social Network provides an exchange with peers.

(e) The "Psych" Tricks feature helps users overcome their habits.

Figure 7: Main screens of Noom (LLC, 2019d)

2.3.5 *Summary and Conclusion*

To summarize our overview of popular commercial nutrition applications, the most considerable research and feature gaps are accuracy and consistency of nutrient information provided for food items, implementation of behavior change techniques, automation of intake tracking, and personalization of content. On the feature side, the analysis of the four most commonly assessed applications results in four core features: food intake tracking, nutrient feedback, (external) activity tracking, and social networking features. While the analyzed applications are targeting an adult population, the derived features are also applicable to applications for children and adolescents when provided through adequately designed interfaces. Both applications for adults and children are dependent on modeling different facets of nutrition in a formal way. Possible models and their limitations are reviewed in the next section.

2.4 NUTRITION MODELLING

To build mobile applications for personalized support of healthy eating, an application needs to track and evaluate a user's dietary intake. Our review of mobile applications shows that most commercial apps support intake tracking using large databases and barcode scanning or even photographic input. However, the corresponding papers warn about the incorrect or incomplete nutritional information of these input sources. At the same time, these applications give visual feedback on the user's calorie and nutrient intake. The data and models underlying this visual feedback are not always scientifically based and might mislead users towards unhealthy or even dangerous diet changes. Finally, many applications do not personalize the feedback on dietary behavior to the individual user, e.g., by including historical nutrient intake or personal BMI. A formal nutritional model needs to integrate food-related, user-related, and health-utility-related concepts to offer trustworthy advice to users. The following sections discuss multiple variants of each of these components their target priorities and their advantages and disadvantages.

2.4.1 *Food Information Retrieval*

Food is a multifaceted item that ranges from commercial supermarket products, such as canned ravioli, over single food ingredients, such as an apple, up to full recipes, such as "Spaghetti Carbonara". Each type of food item is connected to different information sources and can include various descriptive variables. The case of commercial food products is most accessible from an information retrieval point of view. In the European Union, food products need to be labeled with their nutritional content (e.g., fat) (Union, 2011). Some countries additionally provide traffic-light food labels based on the health evaluation of items, such as the Nutri-Score (Chantal et al., 2017). An assessment for German supermarket products (de Edelenyi et al., 2019) showed that the Nutri-Score discriminates well between different food items and aligns with German eating recommendations. The general effectiveness of traffic-light labeling has also been shown in, for example, by Thorndike et al. (Thorndike et al., 2014). The authors show how traffic-lights in a hospital cafeteria increased green item consumption by 5 percent and decreased red item consumption by 4 percent. Additionally, information on price, ingredients, labels, and allergies might be available in some databases. In many cases, all this information is accessible by scanning the barcode and reading from one of the available databases, e.g., Codecheck (Codecheck AG, 2020). A drawback of this type of food item is the coarseness of information. For personalized dietary advice, the inclusion of micro-nutrients might be essential. However, this type of information is only provided voluntarily by some product vendors. Detailed information on nutritional content is available in national nutritional databases such as the BLS, NEVO, or U.S. Department of Agriculture (USDA). The nutritional content of the same items differs between the databases. However, en effort to harmonize between the databases was made in the EuroFir project (EuroFIR, 2020)(Finglas et al., 2014). Another drawback of these databases is the limited amount of available food items and the missing information on attributes such as price or differences by the vendors. The most complex type of food item that can be consumed is a recipe. While recipes are readily available in many databases, these databases rarely provide nutritional content or even structured details on each ingredient's processing state, which is relevant to the nutritional content (e.g., fat) of a meal after processing (e.g., frying). Instead, the single components need to be mapped to their respective entries in one of the nutritional databases, as done, for example, by Müller et al. (Müller et al., 2012). Finally, none of the available databases captures the component of taste. Many recipe databases feature tagging of recipes, e.g., "superfood", "spicy", "traditional". A future sensor might capture food information on both flavor and nutrients on a molecular level. First efforts on such NIR spectroscopy have been assessed by Rateni et al. (Rateni et al., 2017). Both refer to FoodScanner (Spectral Engines Oy, 2018), SCIO (Goldring and Sharon, 2016), as well as a solution by TellSpec Inc. (Watson and Correa, 2015) as prominent prototypes to derive nutrient information on food items. While promising great innovation potential, these technologies are hard to handle by end-consumers, which limits their current applicability to dietary tracking.

2.4.2 *User Profiling*

As shown in the review of nutrition interventions, personalizing advice to user profiles, and intake history is very beneficial. Profile variables can be phenotype and genotype, as in the Food4Me project (Celis-Morales et al., 2015), or microbiomes as in the project of Zeevi et al. (Zeevi et al., 2015). Given that a system has all the nutritional information on food items from different sources, it still needs to retrieve the user's connection to these food items, e.g., intake, preference, or allergies. Intake tracking is vulnerable to many errors depending on the method of retrieval. Commonly used tools for extraction are 24h recall, food frequency questionnaires, and food diaries. Each of them has different advantages and disadvantages (Straßburg, 2010). While food frequency questionnaires are easy to use and do not rely on estimating all ingredients or portion sizes of the current meal, they can only cover average retrospective data and thus suffer from inaccurate or generalized memories. Both recall and diaries can be used daily but suffer from portion estimation errors and pose a lot of effort. Additionally, all types of intake tracking are prone to subconscious under- or over-reporting and perception bias (Gibney et al., 2002). Depending on the study and validation method, different assessment strategies provide similar error ranges. FFQs underestimate energy intake by 11-35%, recall methods underreport energy by 3-34%, and dietary diaries by 4-37% according to an analysis of different studies by Thompson and Subar (Thompson and Subar, 2017). Finally, missing portion size agreement in recipes (e.g., one zucchini) can lead to errors of 50% for actual food intake and up to 20% in nutrients (Margetts and Nelson, 1997). Modern techniques for image-based intake tracking with image recognition are suffering regarding the portion estimation. For example, Zhang et al. (Zhang et al., 2011) report error sized of around 20% for 3D portion estimates. Meyers et al. (Meyers et al., 2015) report similar issues with portion sizes and image recognition for food intake. Another upcoming solution for tracking is the use of smart tools, such as intelligent forks, plates, or glasses, to estimate portion sizes (Kadomura et al., 2014). Finally, intake could be approximated from biological signals such as glucose levels measured with continuous sensors (Gough et al., 2010).

2.4.3 *Nutrition Utility Functions*

Once the user's intake is tracked, and the nutritional information of that intake has been calculated, the personalized advice on health and behavior should be generated. This advice can be based on different levels of detail and different attributes such as food group, calories, macro-nutrients, and micro-nutrients (KANT, 1996). Further aspects that might be relevant, but are not considered regarding healthy nutrition are, e.g., sustainability and organic status of consumed food. The most commonly used non-personalized advice on nutrition is available in national guidelines such as the DGE in Germany (Jungvogel et al., 2013). These guidelines give general hints on what guidelines need to be followed to have a healthy diet, e.g., eat fruits and vegetables five times a day. Many of these guidelines do not state explicit numeric limits or recommendations and are thus hard to model formally. The guidelines often focus on the level of food groups and their relative consumption as, e.g., given in a food pyramid. Furthermore, these guidelines might differ between different organizations and countries. (Montagnese et al., 2015). Finally, as the Food4Me project has shown, "one size fits all" guidelines are less useful than personalized feedback. A more detailed and slightly personalized modeling level is the pure count of calories compared to the burned calories throughout the day. This necessary calorie intake can be determined by the personal basal metabolic rate multiplied with a physical activity factor (Gibney et al., 2002). One level deeper, the number of calories contributed by different macro-nutrients such as saturated fatty acids can be analyzed. One example of such measures is a portion of 7-20% of energy from protein (Lee et al., 2015). Of course, this type of feedback on energy sources can be combined with feedback on the general number of calories. The advantages of this type of modeling are that the macro-nutrient distribution and the number of calories are available for both nutritional databases and commercial products and that the energy content is largely stable under different processing steps in recipes. Finally, the nutritional advice could also incorporate micro-nutrient information, such as comparing optimal and actual intake in vitamin C. Challenges with micro-nutrient estimation are their dependency on processing such as frying, and their lack of data in commercial food items. The health utility of micro-nutrients can be modeled using the Dietary Reference Intake (DRI) of each nutrient (Otten et al., 2006), which covers nutrient deficiency levels and toxicity levels. This type of guideline depends on the user's age and gender and might also differ between organizations and countries. Beyond age and gender, initial research indicates that the utility of nutrients depends on the users' phenotype, genotype, or microbiome. However, such relations are not yet explored sufficiently to be able to formalize any explicit correlations and dependencies (Nordström et al., 2013).

2.4.4 *Summary and Conclusion*

In summary, a formal model of personalized nutritional utility needs to integrate a comprehensive user profile, accurate intake tracking, food information from diverse input sources, and personal utility functions based on nutritional parameters such as nutrients. Depending on the nutrition assistance system's primary goal, various levels of modeling are available for system designers. While personalized nutrition advice is most effective when generated using a detailed model on the micro-nutrient level, an application for children would be more easily understandable on the level of food groups, as delivered by many national guidelines. Uncertainties are inherently included in nutrition modeling, e.g., due to unreliable nutrient information of commercial products, errors in intake tracking, and the fuzziness of nutritional guidelines themselves. Independent of the chosen formalization and input interactions, any health-related mobile application with semi-automated medical feedback is facing additional challenges compared to, e.g., entertainment applications. The following section reviews these challenges on the exemplary case of health recommender systems. Since algorithmic recommendations and their communication via interfaces can be abstracted as automated feedback provided to users, the challenges are transferable to other socio-technical health applications.

2.5 HEALTH APPLICATIONS

Health-related applications are facing many challenges that go beyond questions of algorithmic solutions and usability of application interfaces. Together with the authors of the first workshop on Health Recommender Systems in 2016, these challenges were surveyed and discussed in (Schäfer et al., 2017b). The basis for this review is a collection of papers from 2011 to 2016. The collection of papers was done via Google Scholar with the search term "health recommender systems". The results were reviewed manually for fitting the topic. The final 27 relevant results are categorized in table 2. Over the reviewed timeframe of five years, the number and variety of contributions have increased steadily. While not all papers target nutrition, the underlying challenges remain relevant to this topic as well. The three main areas of challenges evolving from the surveyed papers are the personalization of content, the impact of applications, and evaluation. Each of them is discussed in the sections below. Four other concepts have not fully emerged yet during the survey but were indicated as future work: psychological model, explainability, accountability. Since this survey was conducted, each of these areas has received increasing attention and proven to be an important aspect of health applications and other domains.

Table 2: Using the search term "health recommender systems" on Google Scholar, the authors manually reviewed the relevant HRS publications of the last five years and selected the major concepts from their titles. This table has been taken from (Schäfer et al., 2017b).

Year	#Papers	Top-Concepts
2011	1	HRS, Personalization, Semantic Network
2013	2	HRS, Context-Aware, Health Data
2014	5	Trust-Based, Personalization, Diet, Mobile, User Profiling
2015	9	HRS, Nutrition, Social Network, Mobile, Semantic-Based, Health Data, Patient-Centered
2016	7	HRS, Tailoring, Smoking, Harm, Interactive, Cloud, Expert-In-The-Loop, Sensor-Network, Patient-Centered, Mobile, Social Network, Patient Satisfaction

2.5.1 *Personalization*

The first trend in the survey on health recommender systems papers is personalization. To personalize recommendations of either health-related artifacts, such as medicine, or health-related behavior, such as fitness activities, the user's profile needs extensive information on, e.g., health-related history, current physique, or personal health-related preferences. Such data is not always readily available. The easiest user profiling sources are self-reported input, such as personal preferences, automatically retrievable input, such as social network connections, and measurable input, such as average steps per day. Much less accessible is data such as electronic health records and patient history. Challenges in data retrieval are based on decentralized data-collection, missing standardization, and data-protection. Once the data is retrieved, it needs to be processed into usable patient profiles, as suggested by (Wiesner and Pfeifer, 2010), with abstracted data relevant to the respective recommender. Afterward, these patient profiles need to be compared to extract similar users or items for the recommendations. Lopez-Nores et al.'s HARE (López-Nores et al., 2012) solves this task by extracting information from electronic health records and using them for collaborative filtering based on properties. Based on the fitting of a user's profile, personalized feedback can be calculated and communicated. Personalization can be based on different parameters such as recommending items fitting to a specific illness (e.g., diabetes) as derived from the user's electronic health records record (Luo et al., 2012). One step further, items can be selected after deriving the stage of this illness via the patient history (McClellan et al., 2016). Finally, such an illness progression can be predicted based on the patient history of similar user's (Hu et al., 2016). In that case, fitting medical items can be recommended before the next stage is even diagnosed. Additionally, the recommendations can be communicated based on the patient's personal situation, e.g., by visualizing the history and predictions data. In summary, personalization in health applications is beneficial to the quality of feedback and, in many cases, essential to the safety and applicability of feedback to a specific user/patient. Challenges to this type of personalization are both availability and quality of personal medical data, and the risk of misinterpretation when comparing similar patients with different actual diseases. Concerning the case of nutrition, personalization faces similar issues. While intake data can be modeled in various ways, personal responses to nutrition depending on genes and microbiomes are still challenging in both acquisition of relevant data, and accurate corresponding models.

2.5.2 *Impact*

The second trend in health applications concerns the impact on the user's behavior. Particularly, health applications should often balance influencing the user towards a particular behavior, e.g., using persuasive systems design methods, and leaving the responsibility for actions and decisions with either the user or a health expert. One way of steering the user behavior is the integration of nudges (Thaler and Sunstein, 2008). Reimer et al. (Reimer and Maier, 2016) integrate nudging into health applications tailored to the user's goals and behavior. In their framework, they even personalize to situational contexts. Another example of impacting user behavior with persuasion is the work by Radha et al. (Radha et al., 2016). The authors show how the effectiveness of recommendations for hypertension varies when increasing engagement and motivation. While nudging and persuasion do not immediately manipulate the user, they do incentivize certain behaviors. Without awareness of this influence, the user might not take conscious decisions and thus stays dependent on the system. One way to counteract this effect is by systematically teaching and empowering the users. Hammer et al. (Hammer et al., 2015) offer this type of empowerment by using rule-based algorithms to provide explanations for their recommendations. Additionally, such empowerment strategies can increase the user's trust in the application and thus increase impact. If algorithmically possible, a combination of nudging with explanatory content can thus increase persuasion, empowerment, and trust (Pu and Chen, 2007).

Of course, empowerment and trust also have drawbacks regarding complex medical decisions. Such systems should only be used either with an expert or a *physician in the loop* to prevent, e.g., misdiagnoses (Holzinger et al., 2016). Since nutrition is often closer to lifestyle applications than to critical medical applications (e.g., for diabetes), nudging and explanations are relevant and positive choices for designed systems.

2.5.3 *Evaluation*

The third trend in health applications is the focus on new evaluation methods. Depending on the health domain applications are targeting, these methods can be transferable. Especially for the case of nutrition, traditional interventions can be applied with mobile applications. In contrast to usability and perception measures, the quality of the application would be measured primarily by the effect on the user's behavior and medical outcome measures. Besides nutrition (25%), the most commonly evaluated health areas are that physical activities (42%), smoking (18%), and drinking (9%) (Lustria et al., 2013). One reason for this focus on lifestyle and behavioral application areas is the ethical responsibility of health applications. For medical interventions, any output of the application needs to be safe to follow. Additionally, evaluations of medical applications would require medical outcome measures, e.g., blood values. Instead, lifestyle applications for the health domain can often rely on measuring behavior (Olson, 2016) and are in the scope of the personal responsibility of the participants. Possible metrics that are classically used for evaluating applications might not be applicable to the health domain. For example, the user's desire to eat something sweet might contrast with the application's goal to reduce sugar. Thus, user satisfaction cannot be used as an indication of success. Similarly, health-related advice, especially when not followed, might need to be repeated many times, contrasting with diversity and novelty goals in applications. On the other hand, control and transparency become even more important regarding the above-mentioned concepts of empowerment and trust. Finally, evaluation needs to be conducted in real-life settings, to capture the full extent of contextual influence factors that might not be present in laboratory pre-studies.

2.5.4 *Psychological Models*

The need to incorporate psychological theories, especially on behavior change, was already prominently discussed in the review on both nutrition interventions and mobile applications. The input to such models could be informed by both person characteristics as done by Wiesner et al. (Wiesner and Pfeifer, 2014), or interactions with the system as done by Lathia et al. (Lathia, 2012). Additionally, the user's state in a particular model could be predicted and used for personalization. Several prominent motivational theories can be integrated into applications for changing health-related behavior. One of the earliest models is the health belief model by Hochbaum et al. (Hochbaum et al., 1952). This model explains and predicts health-related behavior with six factors: The perceived susceptibility to a health-related risk, the perceived severity of that risk, the perceived benefits and barriers of the behavior to be adopted, external cues to action, such as advertisements or free tests, and the perceived self-efficacy, meaning the belief in ones own ability to achieve this behavior. Any of these factors can change the impact of health promotion programs to higher or lower acceptance rates. Another theory that includes self-efficacy is the Theory of Planned Behaviour (TPB) (Ajzen et al., 1991), which in itself is building on the Theory of Reasoned Action (TRA) (Fishbein, 1979). The TPB states that any reflective decision is based on three main factors. The actors' attitudes towards the decision, subjective norms, which are reflecting attitudes of the social environment, and perceived behavioral control, which aligns with the self-efficacy mentioned above. All these factors influence the actor's behavioral intention, which then leads to the behavior itself. A theory that is more concerned with motivation types behind an actor's attitude is the Self Determination Theory (SDT) (Ryan and Deci, 2000). According to Ryan and Deci, the two major motivation types that can be distinguished are autonomous and controlled motivation. While many behavior change programs aim at controlled motivation, meaning to offer external benefits for an action, autonomous motivation is more sustainable in the long-term. The authors suggest that autonomous motivation can be achieved when the three basic intrinsic motivation needs are met. These three needs are, namely, competence, relatedness, and autonomy. In terms of another terminology, the authors explain, that intrinsic motivation is always autonomous, while extrinsic motivation can be autonomous if the external motivators are truly internalized. A later theory by Prochaska et al. models behavior not as a decision where motivation leads to action, but as a step by step process wherein each phase needs different motivators and decisions. They divide change into five phases: precontemplative, contemplative, preparation, action, and maintenance. In each phase, some action cues and interventions can ease the transition to the next phase. At the same time, each phase bears the potential to relapse. For example, the feeling of competence and self-efficacy is central to the transition from action to maintenance. On the other hand, relatedness and subjective norms might be more important to transition from the preparation to the action phase. A more intervention focused framework is the behavior change wheel (Michie et al., 2011) with its assignment to fitting behavior change techniques (Michie et al., 2013). The wheel itself is centered around the actor's behavior and its preconditions physical and psychological capability, physical and social opportunity, as well as automatic and reflective motivation. These three core conditions of behavior align well with the dimensions of interest previously described and extend them by going beyond the actor's internal state to include the actor's real-life environment. The challenge lies in adequately mapping the current and targeted behavior to identify the gaps in circumstances and target these explicitly. The framework aligns these gaps and needs with appropriate interventions from different contexts and disciplines such as education.

2.5.5 *Explainability*

Trust is an essential goal in health applications. The trust of users can be increased with transparency and control. One popular way to provide transparency is by using textual or visual explanations of the algorithmic output. One work on explaining recommendations in high-risk domains by Herlocker et al. (Herlocker et al., 2000) notes that this step is necessary due to the sparseness of available data, and the resulting shift in responsibility from the system to the user/patient. Explanations need to be tailored to the abilities of the user. For example, age, pain, stress, and anxiety might lead to reduces processing capacities (Wilcox et al., 2010). Also, the language of explanations needs to be adapted to the target user (Sadasivam et al., 2016).

2.5.6 *Accountability*

While explanations can help the user in making informed decisions (Herlocker et al., 2000), errors in the algorithm or explanations can still lead to disastrous consequences for the health and life of the user. At the same time, giving too much control to the user might threaten the necessary roles of classical health providers such as doctors (Tang et al., 2006). Already, wrong self-diagnosis and self-treatment based on internet searches are a hassle for primary care facilitators. Thus, it is important to keep experts and care providers in the loop when creating and using health applications of a certain risk level.

2.5.7 *Summary and Conclusion*

In summary, health recommender systems, and thus also other socio-technical systems for health, are facing several new challenges. The literature on this topic available at the point of this survey focuses on topics of personalization, persuasion, empowerment, trust, and evaluation methods. The future challenges that have not been addressed yet, further include the integration of psychological concepts for behavior change, explainability of provided feedback, real-life evaluation methods, as well as impact and accountability. The personalization aspect has already been shown to be relevant to the case of healthy nutrition within the review of traditional nutrition interventions. Further, the feedback on missing persuasion, empowerment, and psychological models is in line with the work on currently available commercial applications for nutrition. Finally, while there have been several classical controlled trials for nutrition interventions and several classical user/usability tests for mobile applications, there is little research that combines both aspects into a coherent evaluation of real-life impact provided by socio-technical systems for healthy nutrition.

2.6 REQUIREMENT ANALYSIS AND RESEARCH GAPS

As part of the rigor cycle according to (Hevner, 2007), this chapter assesses important baseline knowledge from nutrition science, on the commercial market, regarding formal models, and about challenges health (recommender) applications. All these areas of expertise need to be considered when designing a new socio-technical system to support the user in making healthier dietary decisions. The analysis of these knowledge bases leads to the following assumptions and design requirements.
Positive effects identified by previous nutrition interventions are:

Requirement 1 Inclusion of self-monitoring and other behavior change techniques
Requirement 2 Combination of diet and physical activity

Requirement 3 Separation of interventions for children and adults
Requirement 4 Use of mobile technology
Requirement 5 Long-term duration of interventions
Requirement 6 Personalization of feedback to dietary habits

Three research gaps mentioned in the reviewed literature are:

Requirement 7 Analysis of and automated feedback on actual intake
Requirement 8 Mitigation of differences in participants' initial dietary habits
Requirement 9 Further investigation on dropout in online interventions

Required high-level features identified from the market review are:

Requirement 10 Intake tracking
Requirement 11 Nutrient feedback
Requirement 12 Activity tracking
Requirement 13 Social support

These four feature requirements are in line with previously identified positive factors of nutrition interventions. Gaps identified in commercial applications lead to three further requirements for the design:

Requirement 14 Providing accurate nutritional information for intake tracking
Requirement 15 Including behavior change techniques
Requirement 16 Personalizing content to user profiles and intake history

The requirements derived from the analysis of nutrition modelling parameters were already included in similar research gaps above. Finally, the review on challenges in health-related applications added two more requirements:

Requirement 17 Explaining provided feedback to enhance trust and empowerment
Requirement 18 Conducting evaluations in real-life settings

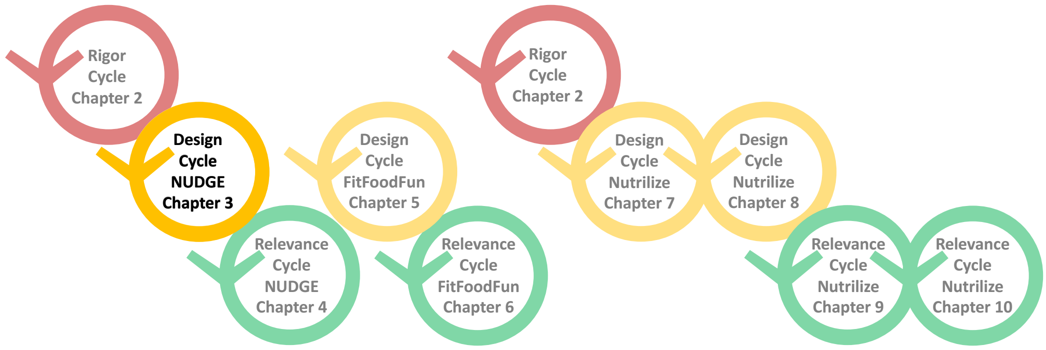
This rigor cycle reviewed the requirements and underlying theories that provide the baseline for all subsequent design cycles. In the summary of this chapter, we derive 18 requirements that guide our socio-technical system's further design cycles. They cover insights into best practice concepts (e.g., behavior change techniques), best-practice features (e.g., intake tracking) of successful applications, and literature gaps (e.g., personalized and accurate nutrient modeling) that have been suggested for future research. Some requirements are more relevant to the case of children and others in the case of adults. The ideas of social support, the combination of nutrition and physical activity, and the use of mobile technology are focused during the design of the *NUDGE* platform in chapter 3. The ideas of personalized nutrition recommendations, internet-based interventions, and mobile food tracking are focused during the design cycles of the *Nutrilize* application in chapter 7.

Part II

CASE NUTRITIONAL GAMES FOR YOUNG ADULTS

3

A SERIOUS GAMES PLATFORM FOR HEALTHY NUTRITION



This chapter elaborates on our serious games platform's design concept, *NUDGE*, and a focus group evaluation of this concept. The first half of the chapter is taken from a publication at ChiPlay's Positive Gaming workshop, of which I am the first and main author, (Schäfer et al., 2017). For legibility reasons, any literal citation of my previous publication within this chapter is color-coded in the same gray color as this sentence without giving a citation to (Schäfer et al., 2017). This chapter opens the topic of socio-technical systems for healthy nutrition in children with the first design cycle. We think broadly in this design cycle and encase many common theories or features derived in the rigor cycle (chapter 2). We derive the idea of a platform for children, including a variety of serious games, a social support network, and a persuasive quantified self component connected to a tracking system. The platform integrates these elements seamlessly, by using a quantified self avatar as the user's gaming avatar and social network avatar, by making some of the serious games playable in the groups of the social network, and by using points earned on knowledge from the games to be reflected in the avatar. This solution aims to support children in any phase of their behavioral change (Prochaska and Velicer, 1997) with the fitting component. This initial design idea is first evaluated in a focus group, which is discussed in this chapter. Some individual components are refined and evaluated in the subsequent chapters.

3.1 MOTIVATION

Overweight and obesity, especially in the younger population, are major health concerns worldwide (WHO, 2014)) According to a European statistic, more than 60% of children that are affected by overweight before puberty will maintain or increase weight in young adulthood (WHO, 2008).

The interdisciplinary *enable* cluster is one of four clusters about nutrition research funded by the German Federal Ministry of Education and Research (BMBF) (enable cluster, 2020). In one of its core projects, *enable* investigates digital communication

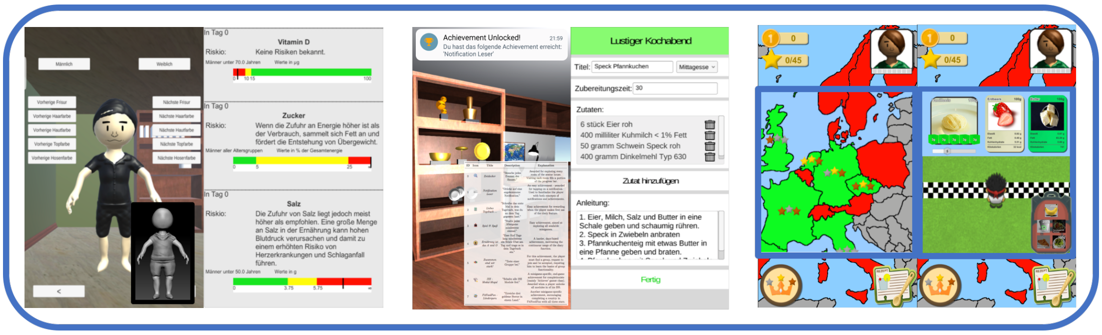


Figure 8: Teaser figure of the *NUDGE* platform. Left: Central avatar element and the nutritional feedback screen. Middle: Motivational nudges and social cooking events. Right: Preview of the serious game prototype *Fit Food Fun*. This figure has been taken from (Schäfer et al., 2017).

strategies to improve nutrition behavior. As a result, the *NUDGE* system is designed as an educative and preventive tool for adolescents to impart nutritional knowledge in a playful and motivational setting. To reach this goal, it promotes health-related outcomes using serious games (Abt, 1987) and different persuasive elements (Oinas-Kukkonen and Harjumaa, 2009).

Besides the imparting of nutritional knowledge, *NUDGE* tries to accompany its users by creating positive feedback loops using both automated and real-world input to ensure the users feel comfortable with their behavioral changes.

3.2 RELATED WORK

There have been several studies on different types of games for health and fitness. (Baranowski et al., 2008a) reviewed 25 video games and found that they are split in their focus on different outcome variables such as knowledge increase and changes in attitude and behavior. *NUDGE* wants to encompass a holistic approach focussing on all of these outcome variables at the same time. This goal is related to the work assessed in the rigor cycle that indicates multi-component interventions being more effective. Therefore, we need to assess various successful design strategies and their impact on each of these variables. We reviewed the following six well-cited serious games regarding their persuasive strategies and health-related goals. In addition to the games' review, different theoretical approaches influenced the design of the *NUDGE* platform. The concept of serious gaming was applied to derive mini-games for nutritional knowledge and skill transfer. The theory of persuasive gaming was used to develop the platform's interaction, such as the avatar and the notification system. The concept of positive gaming was applied furthermore to improve the user's wellbeing during their behavior change.

3.2.1 *Previous Work on Health Games*

One of the first digital nutritional games, 'Packy & Marlon', was designed for children and adolescents with diabetes (Brown et al., 1997). The playing children had to manage the blood glucose levels of two elephants with diabetes by choosing adequate food and insulin quantities. A six-month randomized controlled trial (n=59; age=8-16 years) showed that after playing the user's knowledge about diabetes increased, while the number of urgent hospital visits decreased.

The game 'HungryRedPlanet' (Anderson, 2002) (age=10-15 years) used a similar approach for healthy adolescents by utilizing the USDA Pyramid Guide for healthy and balanced nutrition. Similar to the game "Packy & Marlon", the goal of this game is to manage adequate food quantities to win the game and stop earth's starvation.

The two serious games 'Escape from Diab' (2010) (Thompson et al., 2010) (age=10-12 years) and 'PLAY, MATE!' (2010) (Berkovsky et al., 2010) (n=180; age=9-12 years) focused on persuasion and behavior change in addition to the knowledge transfer. The study of (Berkovsky et al., 2010) showed that games and persuasive elements could increase the physical activity without disturbing the enjoyment of players.

More health games are starting to integrate different persuasive concepts to address different target groups. For example, the National Mindless Eating Challenge (NMEC) (Kaipainen et al., 2012) (n=2053; age=39.8 years in average) integrated comparisons, customization, rewards, personalization and suggestions. Finally, the game 'Move2Play' (Bielik et al., 2012) (n=12; age=12-13 years) provides a setup for physical activity similar to the one *NUDGE* is implementing for nutrition. Move2Play integrates monitoring, goal-setting, a social component, achievements, rewards, and an avatar component. Their small study showed that the children were able to understand all different components of the setup and enjoyed the customizing of the avatar and the social components.

3.2.2 *Serious Gaming*

Gamification as a preventive tool for promoting health-related behavior often lacks efficacy. Many gamification approaches mainly transfer game elements such as points or leaderboards to a non-gaming content (Deterding et al., 2011). In contrast to gamification, serious games offer an active exploration of serious intellectual problems (Abt, 1987). For example, a gamification approach would be to provide users with achievement notifications when they track their diet. However, a serious game would incorporate the nutritional knowledge and offer activities that will contribute to transferring that knowledge actively to the user. Simultaneously, the gaming character is stimulating the user's intrinsic motivation to play and learn (Wong et al., 2007). The primary purpose of a serious game is to transfer knowledge in a playful gaming context (Michael and Chen, 2005). The *NUDGE* platform uses the concepts of serious gaming and motivational stimulation in different nutritional mini-games.

3.2.3 *Persuasive Gaming*

Persuasive strategies are application components that are designed to influence the user's behavior or attitude towards a predefined goal (Fogg, 2002). (Oinas-Kukkonen and Harjumaa, 2009) defined a framework with 28 different persuasive strategies. (Wiafe and Nakata, 2012) reviewed how 44 papers from different domains implemented those different strategies. For the health domain, they came up with the following ten most used strategies: feedback, self-monitoring, suggestion, social role, simulation, tailoring, tunneling, reminders, reduction, and reward.

There are drawbacks to these strategies regarding their applicability to all user groups. A number of strategies only work for a specific selection of personality types. (Orji et al., 2013) and (Kaptein et al., 2012) discuss how using generic persuasive strategies might even reverse the motivational effect for specific personality types. However, strategies such as competition, comparison, self-monitoring, and suggestion seem to be effective on most personality types (Orji et al., 2014). The *NUDGE* platform uses the concepts of feedback, self-monitoring, social role, simulation, tailoring, reminders, and rewards, as suggested by (Baranowski et al., 2013) for all games for health.

3.2.4 *Positive Gaming*

The concept of positive computing was defined by Calvo and Peters (2014) (Calvo and Peters, 2014) and includes three different design approaches. The preventative design methodology attempts to exclude any negative influence of the systems towards the user, while the active design methodology tries to integrate elements that specifically exert a positive influence on the user. Finally, the dedicated design approach focuses on applications that have wellbeing as their primary goal. To implement those design strategies, Calvo et al. (Calvo and Peters, 2014) also suggest different factors such as positive emotions, motivation, self-awareness, and empathy that can be utilized when building positive applications. The *NUDGE* platform follows the argumentation by Calvo et al. (Calvo and Peters, 2014) and implements the concepts of preventative and active design using different intrapersonal and interpersonal factors such as social components and a quantified-self avatar.

3.3 PROPOSED SOLUTION

The *NUDGE* platform is built as a system connecting multiple intervention bricks. The core of the platform is a digital avatar. The digital dietary diary is one of the core features derived during the rigor cycle as necessary for personalized dietary feedback. This personalized dietary feedback is presented to the children via the avatar. The avatar represents the health state of the user based on a digital nutrition diary. The body composition of the avatar reflects weight gain and loss. In addition to physical adaption, the avatar also expresses moods such as hungry, lonely, or excited. These moods should motivate the users to perform specific platform actions such as filling their nutrition diary, interacting with groups, or playing serious games. The avatar can enter different serious mini-games such as the game prototype *Fit Food Fun*, which focuses on the food's macronutrients and energy content. Other platform games address physical activity or micro-nutrient effects. This combination of both exercise and diet focus is another requirement that was derived during the rigor cycle. Additionally, the user is motivated by a social network and real-life challenges, such as group cooking events. The social groups should support the user by satisfying their need for relatedness according to (Ryan and Deci, 2000) and by shifting their subjective norms according to (Ajzen et al., 1991). The user receives nudges about progress events and social comparisons. The following components try to include the mentioned persuasive or positive strategies.

3.3.1 *Survey on Needs and Wishes*

The target group of the *NUDGE* platform are adolescents aged from 14 to 17 years. In preparation for the nutritional game design, two surveys were conducted, with the first one aimed at children aged 12-18 years (Holzmann et al., 2019a) and the second one at young adults aged 18-24 years (Holzmann et al., 2020). The focus of the *NUDGE* platform is the age group 14-17, but the second survey still gives insights into which attitudes are unique in this target group compared to others. The aim was to gain insights into the needs, wishes, and motives of German adolescents regarding nutritional and digital games, to design a target group-specific serious game fostering improved nutrition. Sources such as (DGE, 2000) and (Feierabend et al., 2016) indicate that nutrition information in adolescents is deficient and needs to be promoted. In 2010, the nutrition report of the German Nutrition Society (DGE) revealed that only about 50% of adolescents are adequately informed about nutrition (DGE, 2000). We developed a questionnaire in an interdisciplinary team with expert nutritionists. Questions refer to nutrition communication and knowledge and focus on needs, wishes, and motives regarding digital gaming. Socio-demographic and anthropometric data were obtained as well.

Our survey on children aged 12-18 years (Holzmann et al., 2019a) contained 43 items and was conducted in 6 middle schools in the school district of Rosenheim, Germany. 46.8% of the 293 participants were female. Overall, the assessed nutrition knowledge (4 questions) was deficient, with only 16 children being able to correctly answer all four questions. Although the participants reported playing digital games (85.5%) and some even daily (61%), only half (51.4%) of them wanted to receive nutrition information in digital games. Specific preferences derived for the design of the *NUDGE* platform were a human-like design of the avatar (preferred by 43%), a small group size of up to five members (preferred by 45.5%), and quizzes (preferred by 54.7%) or tasks (preferred by 42.9%) as the main game components.

Our survey on young adults aged 18-24 years (Holzmann et al., 2020) contained 47 items and was conducted online, primarily targeting (81% of participants) university students in Munich, Germany. 73.1% of the 468 participants were female. While apps were desired as a nutritional information resource for some participants (21.7%), the wish for digital games was not that high (10%). These differences in responses further confirm our conclusion in the rigor cycle (chapter 2) that different age groups should be addressed with different socio-technical solutions.

3.3.2 *Avatar as Central Platform Element*

Within the avatar, different persuasion concepts are combined. First, the avatar can be adapted to the user's appearance using different hair, clothing, and color schemes. The designs were specifically chosen to create an emotional connection. This design should increase the caretaking motivation between the users and the avatar (Turkay and Kinzer, 2014) using a schema of childlike characteristics (Glocker et al., 2009). Si-

Figure 9: Two versions of the male avatar with different low (left) and medium (right) weight class and corresponding outfit designs.

multaneously, the avatar visualizes the nutrition status of the user based on a dietary record. If the user eats healthy for more than three days, the avatars bodyweight will decrease, and new clothing designs will be available (see figure 9). The body sizes are limited to 5 stages and were carefully selected to positively depict even the heavier avatar versions to prevent the weight gain from causing negative psychological effects. Besides this visual feedback, the user can also experiment with nutritional effects using a fast forward scenario. This scenario shows the nutrient contents and their implications, in the given future dietary situation (see also (Mück, 2017)). Both approaches utilize the self-quantification and simulation strategies of the persuasive system design (Oinas-Kukkonen and Harjumaa, 2009). Regarding positive computing, the avatar should externalize the user's emotions concerning their healthy/unhealthy behavior and ease negative feedback given by the system, while still motivating through positive feedback. Finally, the avatar serves as a bus between the different serious games. For example, the avatar spends energy by playing serious mini-games to limit the screen time for the participating adolescents. While the user's nutrition based on the dietary record affects the avatars' body composition, the user's real-life physical activity measured by Google Fit API impacts the avatar's energy level (Mishra, 2015). This physical activity is used to increase the avatar's energy and thus represents another real-life connection. Further avatar characteristics, such as the current nutrient level, will be integrated into future serious games, e.g., by decreasing visibility or slowing movement. Besides the avatar's simulation state regarding real-life values such as nutrition and activity, the avatar also shows the platform status. For example, the avatar will show hunger if the user has not updated the diary, and it will be excited if the user has not played any games in a specific time frame. This status feedback serves as a nudge based on the user's motivation through self-competition (Chen et al., 2011).

3.3.3 *Motivational Elements*

Since the *NUDGE* platform tries to encompass real-life behavior change, the virtual avatar and serious games components might not be sufficient to guide the users in their transition. As derived in the rigor cycle, personalization is an important mediator to enhance the motivational effects of feedback. Additional persuasive and positive elements incorporated are thus personality dependent nudges.

Figure 10: Leaderboard within one of the mini-games including personal avatars and three different star medals (bronze, silver, gold).

It has been shown that tailoring nudges and personalizing achievements can increase the motivational effect (Orji et al., 2013). Our personality dependent nudges are based on seven gamer types identified by the BrainHex model (Nacke et al., 2014) and the Big Five personality types (John et al., 1991). Those personality types are used to select the types of nudges that users receive. For example, a seeker in the BrainHex model would receive praise nudges on diary entries, physical activity, or weight loss. In addition to event nudges, there are achievement nudges such as playing all games, or regularly filling the dietary diary.

3.3.4 *Social Elements*

According to (Orji and Moffatt, 2016) 6 of the 21 reviewed persuasive games for nutrition include a social support strategy. In the *NUDGE* platform, social support is given by groups of 5-10 people that share challenges, a leaderboard (see figure 10), and access to social games. The social groups should provide the user with a sense of relatedness to the group, a sense of competence through the joint successes, and a sense of autonomy within the gaming context (Ryan and Deci, 2000). In the case of missing social contacts with similar problems, the system will recommend groups based on age, location, gender, and BMI. The group system, including the group size, group management, and leaderboard, was evaluated in a small focus group with five participants, which revealed positive feedback on the general approaches. The game design and usability were still criticized.

The real-life group challenges are integrated into the platform as social cooking events. This kind of challenge solves multiple issues of real-life challenges. First, it validates the user's action with social feedback. This social feedback provides positive subjective norms and thus might improve future behavioral intention (Ajzen et al., 1991). Secondly, it offers social motivation for the user to win the challenge. Finally, it opens a platform for exchange about the received nutritional knowledge and other platform elements. These real-life group events were evaluated in a small user study with nine participants that conducted six different group cooking events within two weeks (see also (Mayer, 2017)). The study showed that young people are interested in such events. The most effective motivational elements are the leaderboard list, showing the best cooking event/host of each group, the motto (e.g., Blue Titanic Dinner), giving each cooking event a creative aspect, and the ingredient challenges, telling the host to, e.g., involve salmon in the dinner. This preference for competitive feedback is in line with validating the user's sense of competence and self-efficacy (Ajzen et al., 1991).

3.4 EVALUATION

We conducted two focus groups according to the methodology of Tausch et al. (Tausch and Menold, 2015), to validate the concept of the *NUDGE* platform. As a target group, we focused on school children age 14-17 following the KiGGS study (Kurth, 2006). The focus group was conducted in a middle school of the school district of Rosenheim. Participation is by choice and with parental consent. To make the participants feel comfortable, we integrated the focus groups into the regular school setting in between other lectures and lasted two school lectures, including the regular break time. During the focus groups, both the *NUDGE* platform and an exemplary nutrition game (NutrientsServed) were presented in the form of trailers. Both focus groups were recorded, transcribed, and coded (see also (Weiher, 2018)). This section gives an overview of the evaluation and its results. The guideline of questions during the focus groups was based on two main research questions:

1. How can the *NUDGE* platform sustain motivation in nutrition games?
2. How can an exemplary nutrition game impart nutritional knowledge?

An interview guideline was designed to touch on all critical aspects of these two themes. The final guideline consisted of 10 question sections and was revised multiple times in collaboration with both the game and platform developers and the involved nutrition experts. A particular focus has been set on not framing the questions misleadingly. Both the platform and the nutrition game were presented as video-trailers before asking the respective questions. The trailers were iteratively designed and evaluated by a group of students and researchers working on this topic. The final platform trailer was chosen to represent a mixed reality story between the real-world user and the virtual platform avatar. The points that were focused during the trailer are the customization and personalized weight gain of the avatar, the collection of mini-games, the inclusion of a social network, and real-life events. The final trailer of the exemplary serious game presented NutrientsServed. We developed NutrientsServed as a kitchen game about preparing meals according to customer restrictions and health-related parameters (see also (Weiher, 2018)). The focused points are the collection of ingredients and the nutritional information visualized for each of them, the adaption of portion sizes to calorie constraints, and the playful feedback of customers according to health and taste of the resulting dish.

3.4.1 *Participants and Study Procedure*

The focus group was conducted twice with eight participants in each group. All participants were students in a middle school of Rosenheim's school district and between 12 and 14 years old. The participants had an average weight of 59 kg, an average height of 168 cm, and an average BMI of 21. Each focus group was planned for two lecture sessions, resulting in a total duration of 90 minutes, including a 5-minute break. Both focus groups followed the previously discussed guideline. Additionally, all participants were measured for their height and weight. All students were provided with a number to use instead of names when addressing each other to ensure anonymity. Both focus groups were recorded with two devices and additionally protocolled by two independent observers. All question sections were timed to avoid biasing one discussion over another. All participants received a small gift (healthy sweets) as a token of appreciation.

3.4.2 *Data Analysis Methodology*

Both focus group recordings were transcribed and categorized deductively and inductively. The first focus group did not give very verbose feedback and thus only resulted in a transcript of 3719 words. The second focus group participated actively over the focus group's full duration, resulting in a transcript of 9191 words. The coding level is restricted to a minimum of a single phrase and a maximum of a full participant utterance. The deductive coding is based on the interview guidelines, resulting in 16 main categories and 63 subcategories. After the deductive analysis, several sections remained uncategorized. The subsequent inductive coding resulted in 106 new subcategories, mostly attributed to one of the main deductive categories. After both deductive and inductive coding, all feedback utterances were categorized. Utterances can belong to multiple categories. Overall, 279 category assignments were created. Table 3 is adapted from (Weiher, 2018) and gives an overview of the code assignments in the main categories overall and per focus group.

Table 3: Summary table has been taken and adapted from (Weiher, 2018).
Frequency of occurrences of the main categories.
Note: Columns represent values of both focus groups, divided in parentheses for the first and second group. Percentages are rounded ($0.5 - 1.4 \equiv 1$).
Abbreviations: N (Number), C (Categories), P (Participants)

	Main Category	N of C			% of C			N of P		
		Total	Group 1	Group 2	Total	Group 1	Group 2	Total	Group 1	Group 2
1.	Meaning of nutrition	21	1	20	8	1	11	7	1	6
2.	Nutritional knowledge research	9	3	6	3	3	3	7	3	4
3.	Usage of smartphones	18	6	12	6	7	6	12	5	7
4.	Games on the smartphone	17	8	9	6	9	5	13	8	5
5.	Desire for nutritional knowledge	7	4	3	3	4	2	6	3	3
6.	Motivational factors of the gaming platform	21	4	17	8	4	9	12	4	8
7.	Impression of the gaming platform	26	10	16	9	11	9	14	7	7
8.	Usage of the gaming platform	10	5	5	4	5	3	9	4	5
9.	Recommending of the gaming platform	9	4	5	3	4	3	8	3	5
10.	Impression of the game	35	13	22	13	14	12	15	7	8
11.	Usage of the game	27	8	19	10	9	10	14	6	8
12.	Description of the game	31	12	19	11	13	10	14	6	8
13.	Gameplay	5	3	2	2	3	1	5	3	2
14.	Comparison with other games	22	3	19	8	3	10	10	2	8
15.	Elements of a nutritional game	9	5	4	3	5	2	9	5	4
16.	Additional games for the nutritional platform	12	2	10	4	2	5	10	2	8
	$\sum$	279	91	188	100%			16		

3.4.3 *Results*

The final categorization has been evaluated regarding our two main research questions on sustaining motivation with the *NUDGE* platform and imparting nutritional knowledge with serious games. The following sections discuss the main results for each of these questions.

3.4.3.1 *Participant Attitude*

The focus group participants are first characterized using the main categories 1-5. Overall, the participants are interested in and eager to learn about both nutrition and physical activity. They mentioned the importance of balanced nutrition and suggested that reducing fat and sugar should be considered in everyday life. Concerning their smartphone usage, the situations are more bi-polar. While a larger part of the participants is very active in game-play in everyday life, others do not use their smartphones for gaming. However, the participants agreed that they would be interested in learning about nutrition and improving their nutrition. This first assessment of the target group gives positive feedback on the overall idea of providing children and young adults with nutritional information in general and on using serious games for the majority of participants.

3.4.3.2 NUDGE *Platform*

Concerning the first research question of how motivation is provided by using the *NUDGE* platform, participants named several aspects that should be considered in further research in the main categories 6-9. The most critical feedback was a general amotivation due to the low graphical quality of the prototype. The participants' expectations were targeted to the evaluation of commercial games, not prototypes. Positive impressions that should be targeted in further developments were getting an overview of and feedback on one's diet, the combination of multiple games in one platform, and the avatar's weight change feedback. For the avatar part of the participants noted that they would take care of it, while others liked the reflection of the avatar getting slimmer. The personalization of the avatar's look, on the other hand, was not noted. This feature was prominently discussed compared to other features and should be investigated further to answer RQ1. While the participants liked the nutritional feedback to one's dietary diary, they suggested adding step counters to this data collection and visual feedback. This preference is in line with the rigor cycle requirements to include exercise and nutrition at the same time. Social aspects were noted, but not commented further, which might be due to their commonplace occurrence in all commercial applications. A substantial limitation of these insights is the early stage of the prototype and thus the trailer quality, which impeded a full understanding of the concepts. In summary, the avatar concepts and the visual feedback on both nutrition and exercise were the most discussed motivators on the platform.

3.4.3.3 *Serious Games*

Concerning the second research question on how nutritional games can impart nutrition knowledge, the main categories 10-16 stated during the focus group are evaluated. The most frequent positive feedback was on receiving information on nutrient content for a variety of ingredients. The participants liked seeing, e.g., the color scales of nutrients in a burger. The also noted that learning about nutrition in this way is less boring than otherwise. However, they were worried about the long-term challenge. They suggested unlocking new things and working for new features. Further, the usefulness of this game compared to regular games was mentioned by many participants. Concerning the game aspects, the participants liked that the game combines a lot of freedom and exploration with being challenged and pressured. The general impression of the game was positive. Finally, the participants mentioned wishes for future developments, such as simplified interactions, aesthetic design, the balance between learning and entertainment, and settings and customizations. In summary, we learned that the target group is interested in learning about nutrients in their food via gameful interactions. However, they emphasized that these games need to be challenging and evolve to keep their long-term interest.

3.5 CONCLUSION AND NEXT STEPS

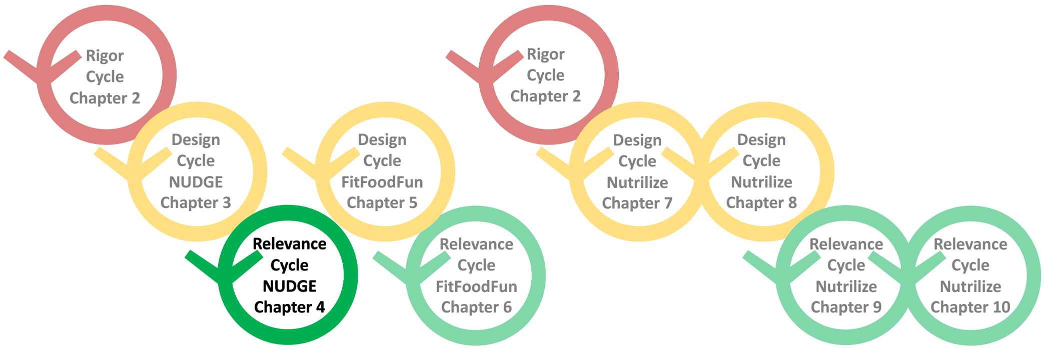
The focus groups indicated that the concepts of both the *NUDGE* platform and its nutritional mini-games spark interest in the target group. Concerning the platform, especially the feedback on personal diet and the avatar were focused by participants.

These two components are further investigated in a pilot study in chapter 4. Concerning the serious games which should be provided on the platform, the participants wish for information on nutrients of ingredients, progressing challenges, as well as good graphical design. All these wishes are further investigated and integrated during the game design of the *Fit Food Fun* game in chapter 5.

In this chapter, we designed *NUDGE* as a platform for healthy eating in children. We provide design concepts for different requirements derived during the rigor cycle (chapter 2). We integrate requirements on self-monitoring and personalized feedback into an avatar concept. Further, we integrate both diet-related and physical activity-related content into a collection of serious mobile games. Finally, we address differences in initial knowledge and the need for social exchange within a group matching system. As shown in this chapter, the holistic platform for healthy eating envisioned in this first design cycle was perceived well by the targeted group of children between 14 and 17 years. The main insights gained from the focus groups are a positive attitude towards the avatar concept, and a critical perspective on the diversity and long-term interestingness of the gaming concepts. The subsequent chapters focus on these two ideas. Chapter 4 does an initial relevance cycle on the avatar concepts in the area of physical activity. Chapter 5 iteratively designs and refines one serious game concept, which is assessed in another relevance cycle in chapter 6. Initial design iterations have been conducted for the social component of the *NUDGE* platform, but these components will not be further evaluated in this thesis's scope.

4

MOTIVATING BEHAVIOR CHANGE USING AN AVATAR



This chapter discusses the results of a study testing the motivational effect of an avatar as a design element of the *NUDGE* platform. This chapter is entirely taken from a late-breaking-results paper at UMAP 2018, of which I am the first and main author (Schäfer et al., 2018). For legibility reasons, any literal citation of my previous publication within this chapter is color-coded in the same gray color as this sentence without giving a citation to (Schäfer et al., 2018). The study discussed in this chapter focuses on the avatar, one of the three design components of the *NUDGE* platform derived in chapter 3. The focus group participants happily accepted the concept of an avatar, reflecting one's actions and state. Thus, we want to take one step further and evaluate the avatar's impact in a relevance cycle. This relevance study aims to assess children's physical activity changes when providing avatar-based feedback on the current/past physical activity. The physical activity assessment was chosen instead of nutritional intake tracking due to the comparatively easy automatic/non-invasive assessment of tracking data. We define a physical activity user model that uses smartphone sensor data to learn the children's activity level according to classes of Metabolic Equivalent of Task (MET) scores. We conduct a user study using a pre-/post-test design with 61 children to measure the predicted activity classes' accuracy compared to accelerometer data. Nineteen of these children receive gamified feedback on their activity level using a mobile application. We analyze how the effect of the motivational interface compares to influence factors. This work combines user activity modeling with motivational interfaces and offers insights into the limits and chances of applications designed for children.

4.1 MOTIVATION

For many children, achieving the recommended level of daily physical activity is a significant challenge. This struggle is a problem, as especially the activity level and nutrition at young ages may have serious impacts on health risks in older ages

(Craigie et al., 2011). For children and adolescents, the WHO recommends at least one hour of moderate physical activity per day (WHO, 2010). The KiGGS study reveals that in Germany, only 27.5% of the children and adolescents aged between three and 17 years fulfill the recommendation of the WHO. Children have been shown to achieve good tracking accuracies when tracking their activity (Trost, 2007). Our work explores the effects and limitations of tracking children's activity and giving gamified feedback on it.

Tracking is a popular measure to increase physical activity and offers increased awareness of previous activities and motivates the users by giving measurable goals (Ridgers et al., 2016). Tracking offers the opportunity to personalize an application to the current level of physical activity and its previous history. Gamification can be an effective intervention in motivating children to increased physical activity (Baranowski et al., 2008a). The combination of activity tracking and personalized gamified feedback can thus offer benefits for a younger target group.

Children do not commonly use accurate tracking devices such as accelerometers or wearables. Additionally, the visualization of raw step counts or other activity measurements might be difficult for children to interpret. Many of the existing activity games that include tracking data are commercial applications (Amresh et al., 2017, Guthrie et al., 2015). Scientific studies on such tracking gamification have been conducted, e.g., with adults (Lin et al., 2006) or for a limited number of days (Johnsen et al., 2014).

One way to overcome the cost and inconvenience of tracking devices is to use readily available smartphone sensors. The sensor data can be integrated into a machine learning model to predict interpretable classes of physical activity. This model should be measurable in terms of health recommendations to provide a daily goal. One popular way to visualize such a physical activity model and to motivate more activity is to use an avatar (Johnsen et al., 2014, Lin et al., 2006, Tong et al., 2015, Kniestedt and Gómez Maureira, 2016).

In this paper, we contribute the design of a user model for daily physical activity levels in children and a motivational interface to communicate this model. The designed application is intended to serve three key questions that we analyze in the form of a pre-/post-test user study. First, how can we accurately train activity models for children based on smartphone sensor data? Second, how do gamified interfaces and other motivational factors influence physical activity? Third, how do the children perceive the tracking and its visual representation?

4.2 RELATED WORK

This section reviews work on physical activity tracking and health recommendations for physical activity followed by work on gamification for physical activity.

4.2.1 *Physical Activity Tracking*

The accurate assessment of children's physical activity is a key component in the field of public health. The effectiveness of interventions or public campaigns cannot be correctly evaluated without access to valid measurements (Warren et al., 2010).

Accelerometry has become a widely-used method to measure the physical activity of people of every age. Compared with subjective approaches like questionnaires, interviews, and diaries or other objective methods like heart rate monitors or pedometers, accelerometry is one of the best methods regarding its accuracy and its feasibility (Trost, 2007).

Most accelerometer types do not have a display and thus do not give direct feedback to the person using it. In general, the motivating effect of self-monitoring has been shown to be an effective tool for increasing physical activity (Michie et al., 2013). Therefore, devices not only assessing the participants' activity but also giving feedback to motivate the participants to be more active are of great interest (Fritz et al., 2014).

However, only a few studies examined the specific effect of wearable activity trackers on the physical activity of children and adolescents. In a recent review, Ridgers et al. (Ridgers et al., 2016) concluded that intervention effects are positive with feedback features being an important factor for children and adolescents.

4.2.2 *Physical Activity Recommendations*

According to the WHO, physical inactivity is the fourth-highest risk factor for global mortality with a rate of about six percent. Physical activities provide fundamental health benefits for children at the age from 5-17 years (WHO, 2010). Physical activities can be measured and categorized using the MET unit: One MET is a physiological measure for the energy used to perform physical activity and is equivalent to $4.841 \frac{kJ}{kg*h}$. Light intensity activities are defined to have a MET below 3 (e.g., desk work). Moderate physical activity is defined as activities that consume 3-6 MET (e.g., walking with 4.8 km/h). All activities that consume more than 6 MET are defined as vigorous (e.g., jogging). For children and adolescents the WHO recommends Moderate- to Vigorous-Intensity Physical Activity (MVPA) at least 60 minutes per day and vigorous-intensity activities at least three times a week (WHO, 2010).

4.2.3 *Gamification for Physical Activity*

There are several investigations on gamification for health (Cugelman, 2013, Fritz et al., 2014) with a number of games focusing on physical activity (Tong et al., 2015, Consolvo et al., 2008). On the commercial side, FitBit Garden (Amresh et al., 2017) is a game dependent on children's FitBit activities. In a study, this game received positive feedback on its usability from 10 children and their parents after a testing period of two weeks. Another one is the Zamzee platform that introduces gamified and monetary rewards depending on the physical activity tracked with their device (Guthrie et al., 2015). Over six weeks, they receive an activity increase of over 50% in 11- to 14-year-old children (Guthrie et al., 2015). Two of the most similar studies to this paper are the Johnsen's virtual pets (Johnsen et al., 2014) and Lin's fish avatars (Lin et al., 2006). In (Johnsen et al., 2014), the children of a summer camp (n=61) are offered access to virtual pets. These pets will learn new tricks depending on the tracked activities. This study shows a 60% increase in physical activity in the first 72 hours. In (Lin et al., 2006) a pre- and post-test study is conducted with 19 adult participants.

The study consists of a 4-week pre-test, a 6-week intervention, and a 4-week post-test. The participants receive a virtual fish pet that changes emotion and weight depending on the tracked activities. 14 of their participants show advancement in the levels of the transtheoretical model (Prochaska and Velicer, 1997), a higher number of daily steps, or both.

4.3 PROPOSED SOLUTION

4.3.1 *Smartphone Activity Model*

The first step to derive a suitable activity model is to collect smartphone sensor data during typical activities. Afterward, a machine learning model is trained to predict predefined activity classes from the collected sensor data. The classes are reviewed regarding their accuracy level and their importance for feedback.

4.3.1.1 *Data Collection*

The collected data contains a set of 56 children from two 6th-grade school classes performing predefined activities within one sports lesson of 45 minutes. Both classes are from the same school in Bavaria, Germany. The data is collected using an early prototype of the feedback system that had been preinstalled on different smartphones to simulate the diversity in children's devices. The performed activities are sitting (8 min), standing (5 min), walking (5 min), jogging (5 min), walking upstairs (4 times 10 s), walking downstairs (4 times 10 s), and intense physical activity (5 min). During the processing, each activity session had to be trimmed by 5-10 seconds at the beginning and end, due to delays in the recording time. The recording of upstairs and downstairs data is influenced by the limited space on the available staircase. The recorded data is split into windows of three seconds with an overlap of 50% to the next window. Each second consists of a sample of ten sensor measurements leading to a sample size of 30 measurements per window.

4.3.1.2 *Training of Machine Learning Model*

The recorded sensor data is used to predict the current activity class for each window of three seconds. The classification models are Support Vector Machines (SVM) and Random Forests (RF). The accuracy measurements for different granularity levels of the activity classes are shown in table 4 (3-fold cross-validation).

Table 4: Prediction accuracy for classifications using SVM with an RBM kernel and RF with 30 estimators. The table has been adapted from (Schäfer et al., 2018).

Predicted classes	SVM	RF
A1: Standing, Walking, Jogging, Intense	77.5%	91.6%
A2: A1 + Sitting	70.9%	85.9%
A3: A2 + Upstairs, Downstairs	65.6%	74.1%

All classifications reach better accuracy measurements using the RF predictor. The accuracy is diminished when adding more granular classes. The accuracy loss for the addition of a sitting class is expected since the children are not required to wear their phones in specific positions. The accuracy loss for the addition of walking on stairs is higher than in literature (Ravi et al., 2005) due to the space limitations when recording this data. Previous work achieves better results (Khan et al., 2013,Sun et al., 2011) regarding the accuracy, since those experiments are conducted with specific devices, fixed phone positions, and adult participants. However, for the integration into our tracking system, the model is required to deal with mixed positions and devices. For the final experiment, the classification is reduced to sitting, standing, walking, and intense activity. The accuracy loss when including the sitting class is considered acceptable because of the added value this information is assumed to give to the children when receiving feedback.

4.3.2 *Visual Feedback System*

The gamified feedback system is given by a simple visualization of the derived activity classification and an avatar model designed to give motivational feedback depending on the current activity levels and their previous history.

4.3.2.1 *Visualization of Activity Classification*

The recorded sensor data is classified each night. The resulting daily distribution of minutes per activity is visualized as a bar chart. The activity classes are shown in increasing order of intensity (from sitting to intense activity) and labeled with the total time for each activity class. The purpose of this feedback mechanism is to increase self-awareness of one's own activity levels. Additionally, the graph allows the children to understand the changes in their avatar's feedback and behavior.

4.3.2.2 *Gamified Feedback using an Avatar Model*

The gamified feedback is based on a level system with five steps reflecting the amount of physical activity during the previous day. The current physical activity level of the avatar is based on the number of minutes per activity class: sitting, standing, walking, and intense. Sitting and standing minutes are evaluated with an activity level of 0.0. Walking is considered with a factor of 1.0 and intense activity with a factor of 2.5. The overall activity value is calculated by adding the weighted minutes of each class. The lowest level covers any user that reaches less than 30 weighted minutes of activity while the highest level only starts once a user reaches more than 120 weighted minutes of activity.

To motivate the children, their gamified activity level is depicted by a personalized animated avatar. The avatar is represented by two animation figures from current children's movies, depending on the gender of the participant. Each level of activity shows a different animation. For example, the male level 1 depicts the avatar lying on a sofa. In addition to the animation, the avatar shows a randomly selected motivational message that depends on the current activity level and on the change in

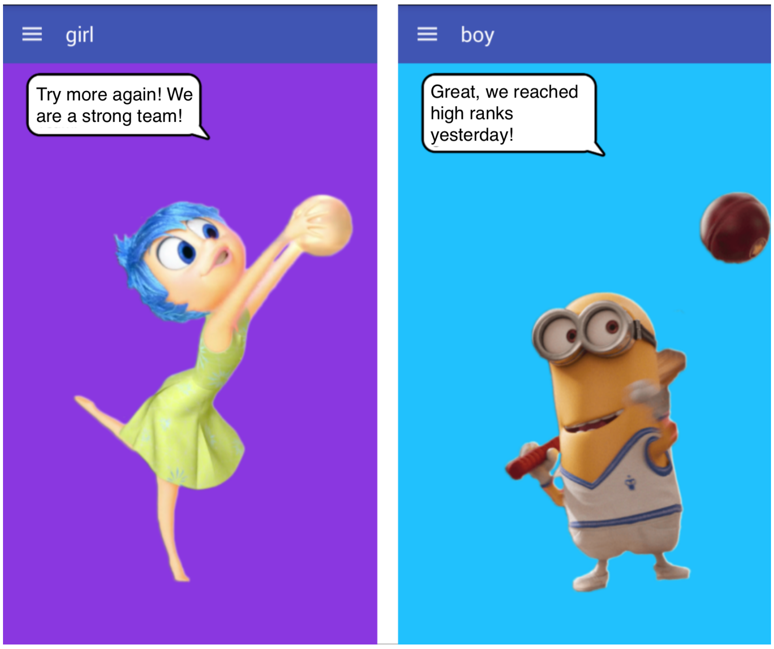


Figure 11: Screenshot of the (translated) gamified avatar. This figure has been taken from (Schäfer et al., 2018).

activity compared to the previous day. Figure 11 shows an example of the resulting design for level 4.

4.4 EVALUATION

To investigate the three key questions, a pre-/post-test design with a control and an intervention group is developed (Ethics ID: 155/16 S). During the pre- and post-test, the physical activity of each subject is measured over five days with an accelerometer (Actigraph GT3X model) that is mounted to a belt and worn around the waist. The intervention phase is specified to take four weeks. During the intervention phase, one group installs and uses the designed application on their private mobile phones.

To test the trained model, the predicted activity levels are compared to the accelerometer data. To test the influence of the application, the change in daily MVPA from pre-test to post-test is compared between the intervention group and the control group. To compare other influence factors, a survey is conducted during the pre- and post-test. To analyze the user's acceptance of the application, the intervention participants fill out a short survey about their experience. Additionally, a sub-sample of participants is interviewed about their experience with the application.

4.4.1 *Participants*

The study is executed in 6th-grade classes of the school district of Ebersberg, Germany. Participation is by choice and with parental consent. The distribution to control and intervention group are randomly assigned with the condition that the intervention participants need an Android-based smartphone. Of the 92 participants, 61 complete both pre- and post-test. 21 participants are assigned to the intervention group but do not meet the intervention group criteria. 6 intervention participants fill out the survey but do not send activity data to the server. 4 participants use the application but are not present during the survey. This participation leads to 13 activity data sets, 15 application surveys and 46 control group participants.

4.4.2 *Study Process*

For the pre-test, both groups receive accelerometers to wear for five days throughout all activities. The participants also have to fill out a questionnaire on their attitude towards physical activity.

During the intervention, one group is handed the application that should be used during the next four weeks. The control group does not receive treatment during those four weeks.

For the post-test, both groups receive accelerometers to wear for another five days. After the five days, all participants fill out the pre-test questionnaire again. The intervention group receives an additional questionnaire about the application.

After finishing the post-test survey, six of the participants in the intervention group are randomly chosen to conduct a short individual interview on their experience with the application.

4.4.3 *Collected Data and Processing*

The accelerometer wear time is validated using the Choi algorithm (Choi et al., 2011). Afterwards, the activity classes are derived using the Evenson Children algorithm (Evenson et al., 2008). This preprocessing results in the average daily MVPA minutes for each participant during the pre- and post-test phase.

The questionnaires comprise several scales. The children's type of motivation to be physically active is measured by the behavioral Regulation of Exercise Questionnaire-2 (Markland and Tobin, 2004). The intrinsic motivation to do sports is assessed in more detail with the 16 items of the German Version of the Physical Activity Enjoyment Scale (PACES) (Jekauc et al., 2013). Sports-related autonomy, competence, and relatedness are assessed with twelve items based on the Basic Psychological Need Satisfaction scales (Chen et al., 2015a). Finally, children's barrier's self-efficacy concerning physical activity is measured with eight items (Dishman et al., 2010). Except for the PACES, every scale is translated to German and linguistically adapted to the age group. Each item is responded to on a five-point scale, and all scales are aggregated as the mean of the subscales.

The smartphone applications collect only the linear acceleration sensor data. Sensors require too much power or are not available on all phones (LLC, 2016). From the linear acceleration data, each second is classified using the trained RF algorithm. The MVPA minutes for each day are derived by adding up all predicted MVPA seconds.

During the interviews, the conducting investigator takes notes on the feedback for each question. Afterward, the interviews are compared and the frequency of similar points is added to the description.

4.4.4 *Results*

The study enables us to compare the activity level predicted by the RF model to the standardized accelerometer data. The survey data gives additional insight into the perception and attitude each participant had in terms of physical activity. We analyze how different attitudes and the application influence the change in physical activity. Finally, we analyze the feedback received towards the application during the additional survey and the interview sessions.

4.4.5 *Activity Modelling Accuracy*

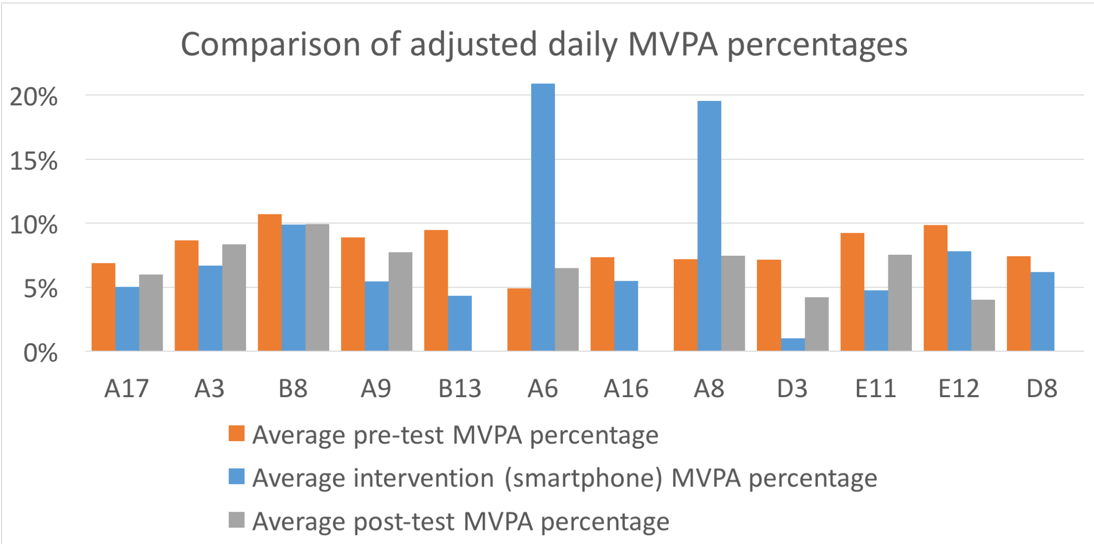


Figure 12: Comparison of MVPA percentages in each phase. This figure has been taken from (Schäfer et al., 2018).

Figure 12 shows the average percentage of daily MVPA minutes in the intervention group. For each participant, we compare the pre-test, post-test, and the predicted intervention activity. Participant D4 had to be excluded due to missing data. Participants B13, A16, and D8 did not offer a post-test dataset, but can still be compared in terms of the pre-test dataset. Of the twelve participants, only two (A6 and A8) showed highly increased activity measurements when using the application. The other participants demonstrate a slightly (1-5%) lower MVPA measurement during the intervention phase.

Having a closer look at the predicted daily MVPA percentage for the two irregular participants, both A6 and A8 show measurements for less than half of the intervention days. A6 stops using the application, and A8 shows missing and irregular (±20%) measurements. In contrast, figure 13 shows the plot of one participant (A9) that provided regular application data. Here the measurements have a reasonable variance of ±5% and show a regular change between slightly elevated and decreased activity.

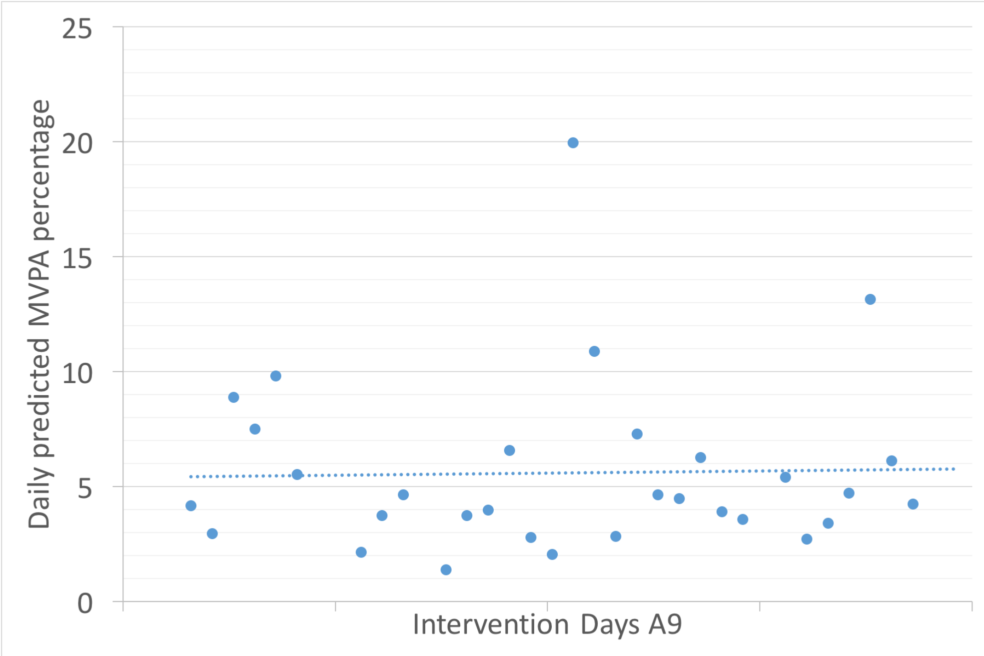


Figure 13: Daily MVPA percentage predictions of A9. This figure has been taken from (Schäfer et al., 2018).

4.4.6 *Analysis of Influence Factors*

Figure 14 shows how the average number of daily MVPA minutes changed in the different groups between the pre- and post-test. In addition to the intervention and control group, we also distinguish the group that was transferred from the intervention to the control group due to technical constraints. All groups show a decrease in physical activity between the pre- and post-test. Both the intervention and control group have similar pre-test measurements close to the WHO recommendation of 60 MVPA minutes. The group that has been changed to the control group starts out with an average of 57 MVPA minutes. At the time of the post-test, both the initial control group and the added control group show a reduction to about 52 MVPA minutes. The intervention group maintains an activity level of 59 MVPA minutes. Dimitrov and Rumrill (Dimitrov and Rumrill Jr, 2003) show the advantages and disadvantages of several evaluation methods for pre-/post-test studies. In line with their analysis, we decide to use an Ancova analysis on the post-test activities with the pre-test measurements as a covariate. When using the Ancova analysis on the final post-test activity, we see that the intervention showed no significant effect on the overall activity.

We also consider motivational factors that might influence the activity change. Table 5 shows the results of the survey in both pre- and post-test for each subgroup of the study. No measurement shows significant differences between the pre- and post-test or between the different groups. When conducting the Ancova analysis with adding the survey factors as covariates, we see that the perceived competence of participants (Pr(>F)=0.0273) and the intervention treatment (Pr(>F)=0.0059) have a strong effect on the change in MVPA. This interaction is in line with (Lin et al., 2006),

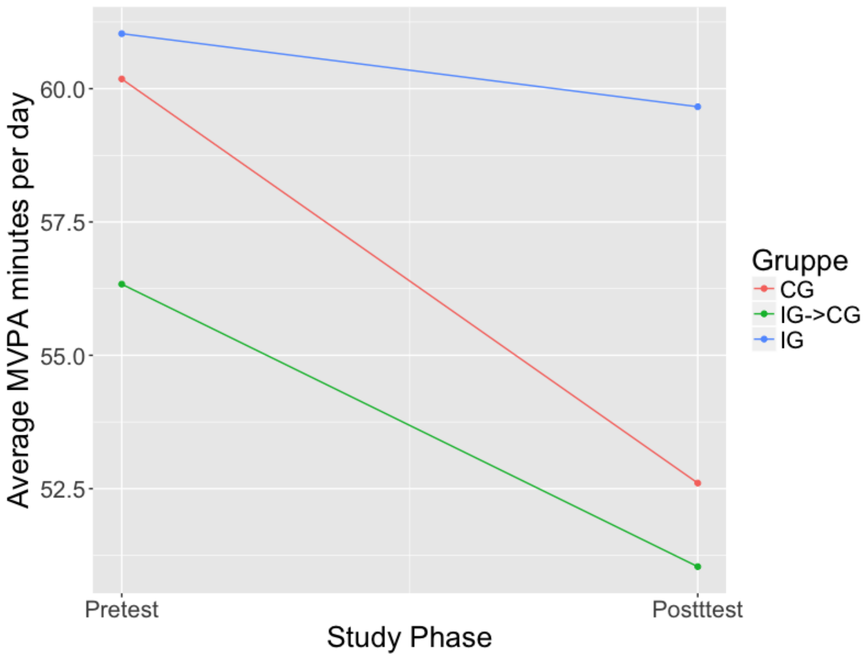


Figure 14: Loss in MVPA time between pre- and post-test. This figure has been taken from (Schäfer et al., 2018).

where participants with a higher transtheoretical level (Prochaska and Velicer, 1997) are less likely to change their activity level. We thus conducted a Ancova analysis that controls for both pre-test MVPA and competence (table 6). In this analysis both competence and the intervention treatment show significant effects on the post-test MVPA.

4.4.7 *Feedback on the Application Design*

Table 7 shows the results of the application questionnaire. The frequency of usage is quite high, with a mean of 3 equaling a frequency of almost every day. All other questions are asked using a five-point Likert scale. The results mostly show an average agreement of 3 with a variation of 1 to 1.5. The lowest agreement is given to the app motivating more activity (2.43) and causing more activity (2.0). The highest agreement is given to telling friends outside the study group about the application (3.64). During the interview, the children are asked about feedback on the app, external comments, and about their own usage over time. Regarding the application experience, most participants report problems with the feedback of the application and do not see the expected change in activity minutes or in the avatar's status. One participant also reports that the application takes too much storage on the phone, causing him to remove it. Finally, two participants do not like wearing their phone in their pocket, especially during physical activity. Five participants report to like the animated avatar and the ability to personalize its name and to influence its movements. Two participants emphasize liking the motivational texts that are shown with the avatar. Two other participants like the visualization of the activity classes and goals.

Table 5: Result of survey measurements for each group. This table has been taken from (Schäfer et al., 2018).

Group	Control	IG -> CG	Intervention
Amotivation Pre-test	0.35±0.53	0.14±0.35	0.37±0.67
Amotivation Post-test	0.24±0.59	0.35±0.95	0.47±0.74
External Pre-test	0.88±1.12	0.43±0.51	0.65±0.65
External Post-test	0.83±1.10	0.50±0.79	0.48±0.55
Introjected Pre-test	1.07±1.13	0.43±0.52	0.84±0.58
Introjected Post-test	1.18±1.07	0.65±0.91	1.11±0.64
Identified Pre-test	2.70±0.68	2.50±0.99	2.72±0.80
Identified Post-test	2.37±0.76	2.74±0.93	2.52±0.86
Intrinsic Pre-test	3.12±0.86	3.30±0.74	3.19±0.86
Intrinsic Post-test	2.91±0.89	3.37±0.71	2.83±1.06
PACES Pre-test	4.25±0.63	4.37±0.55	4.30±0.66
PACES Post-test	4.20±0.57	4.40±0.61	4.20±0.69
Autonomy Pre-test	4.20±1.01	4.34±0.72	4.33±0.72
Autonomy Post-test	4.17±0.75	3.98±1.09	4.43±0.59
Competence Pre-test	3.98±0.73	3.85±0.81	3.47±1.17
Competence Post-test	4.04±0.86	4.01±0.81	3.58±1.19
Relatedness Pre-test	3.78±0.80	3.45±1.06	3.53±0.96
Relatedness Post-test	3.66±0.88	3.43±1.36	3.37±1.29
Self-efficacy Pre-test	3.55±0.78	3.75±0.79	3.58±0.62
Self-efficacy Post-test	3.69±0.82	3.49±1.12	3.47±0.70

Table 6: Ancova with posttest-MVPA as dependent variable. This table has been taken from (Schäfer et al., 2018).

	Sum Sq	Df	F value	Pr(>F)
(Intercept) .	580.74	1	3.82	0.0555
Pre-test MVPA ***	7572.52	1	49.85	2.522e-09
Mean Competence ***	2435.42	1	16.03	0.0002
Intervention Group *	999.86	1	6.58	0.0130
Residuals	8658.36	57		

Three participants request more variety in the avatar's movement and motivational texts. Two participants wish for improvement of the tracking accuracy. Regarding external feedback, all agree that the app was never mentioned in class and that most participants received positive feedback from their parents. Regarding the changes in app usage over time, three participants report using the app in the same way over the

Table 7: Results of the application feedback questionnaire. This table has been taken from (Schäfer et al., 2018).

Question	Agreement
How often did you use the app?	2.57±0.85
Was wearing the phone difficult?	2.80±1.57
I had fun using the app	2.93±1.22
I liked the app	3.33±1.11
The avatar moved more when I moved more	2.79±1.48
The app motivated me to move more	2.43±1.09
I feel like I move more because of the app	2.00±0.82
I like to show the app to friends	2.86±1.51
I told friends outside of class about the app	3.64±1.22

whole phase while the other three report losing interest due to the lacking changes in the avatar.

4.5 DISCUSSION OF RESULTS

4.5.1 *Activity Tracking Using Smartphone Sensors*

The initial machine learning training shows that smartphone sensor data-based predictions can be trained by measuring predefined activities and reach sufficient accuracy levels. The required accuracy can be achieved by using only linear acceleration at a low sampling rate. This sensor restriction is especially important to preserve energy. During the experiment, most predictions based on smartphone sensors are lower than the accelerometer measurements but close to them. This underestimation can be expected, as the accelerometer continuously records every activity, while the smartphone relies on the user carrying and recharging their phone. Some participants report removing the application due to storage or battery constraints. Despite the accuracy evaluation, the general underestimation is perceived by the participants. Some participants mention low activity values after active behavior. This underestimation should be estimated and integrated as a correction factor.

4.5.2 *Effect of Gamified Activity Feedback*

The analysis shows that the application can influence physical activity. The pre-test data suggests that already the participation in a study and the initial accelerometer tracking increase physical activity in both groups. The post-test data shows that such motivation decreases when tracking the second time. On average, the application can slow down this decrease. This observation suggests that interventions for physical activity should be analyzed over longer episodes to avoid measuring initial motivation boosts. Additionally, the effects are strongly influenced by the participant's perceived competence in physical activity. This influence is even more prominent than the influence of the application. This result suggests that applications should be personalized to participants with different competence levels. One solution could be to adapt the suggested goals to their current performance level.

4.5.3 *Perception of Gamified Activity Feedback*

The participants are divided in their perception of the application. While the tracking and the visualization as an avatar are perceived positively, the variety is not perceived as being sufficient for four weeks. This issue of long-term interest has also been discussed in previous work (King et al., 2013, Richards et al., 2014). The repetitiveness leads to lower adherence and, in some cases, to dropout. The children do also not perceive any change in their activity, although this change is visible in their post-test measurements. Additionally, the target group experiences a high amount of technical issues. Issues with battery life are more common since many children had older devices. Issues with storage are more difficult to resolve since some children had no previous experience in freeing space on their phone. Internet access is sometimes difficult due to conflicts with parental guidelines. All these issues indicate that applications targeted for usage by children need to be especially considerate in terms of technical usability.

4.6 Conclusion and Next Steps

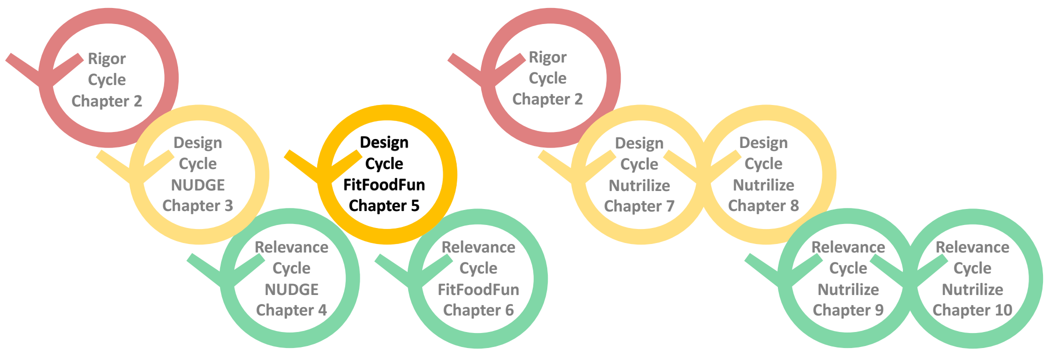
This work is motivated by the potential of smartphone-based physical activity tracking and gamified personalized feedback for children. We show that physical activity classes can be predicted from smartphone data with an accuracy of 85.9%. During the final experiment, the predicted activity data shows a slight underestimation for children that use the application regularly. We design an avatar model to give gamified feedback on the user's activity data. This model is experienced positively by all interviewed participants. The study shows that the gamified interface helps the participants to keep up the initial boost in physical activity. The study also shows that the change in physical activity is influenced by the children's competence level. Finally, the interviews show issues with the underestimated activity, the repetitiveness, and technical problems.

Overall, the investigation shows promising effects. In the future, we investigate interface aspects for long term motivation. Furthermore, the tracking should be improved by a correction factor to avoid underestimation. Finally, we want to extend the personalization by adapting the goals to the user's competence.

In this chapter, we conduct a relevance cycle on the avatar component of the *NUDGE* platform by conducting a pre-/post-test study. The study shows that the avatar feedback helped maintain the initial boost in physical activity, while the control group showed a drop in physical activity between pre- and post-test. Furthermore, the study revealed differences in the main effect, depending on the perceived competence of participants. The participants' feedback indicates that the avatar component is not diverse and interesting enough over an extended period. We thus focus more closely on the platform's gaming component in the subsequent design (chapter 5) and relevance (chapter 6) cycles.

5

DESIGNING A SERIOUS GAME FOR HEALTHY NUTRITION



This chapter focusses on the gaming component of the *NUDGE* platform (chapter 3), by conducting a second design cycle with multiple iterations. The design is based on the general requirements derived in the rigor cycle (chapter 2) and additionally grounded in a review of related work on the context of serious games for health. We discuss why the *Fit Food Fun* game was selected for further design iterations from an initial selection of serious games. We demonstrate the initial design concepts based on three mini-games in different countries on a journey through Europe. The first mini-game compares food items from the current country regarding their macronutrient and caloric content. The second mini-game focusses on the estimation of discouraged nutrients, namely sugar, fat, and salt. The third mini-game targets a better understanding of the balance between energy expenditure during physical activity and energy supply from food items. We elaborate on each of the iterative improvements to this *Fit Food Fun* game. Concerning the pedagogical structure, we discuss the improved alignment of the game's buildup with the AVIVA (Städeli, 2013) and ARCS model (Keller, 2009). Concerning the formalization of nutritional knowledge within the game mechanics, we discuss the selection of DGE rules that can and should be communicated throughout the game. Finally, regarding the user experience, we test and refine the mini-games' difficulty and understandability.

5.1 MOTIVATION

Part of the requirements derived during the rigor cycle in chapter 2 are already covered by the overarching *NUDGE* platform and the avatar concept:

1. Separation of interventions for children and adults
2. Long-term duration of interventions
3. Use of mobile technology
4. Inclusion of self-monitoring and other behavior change techniques
5. Combination of diet and physical activity

6. Personalization of feedback to dietary habits
7. Intake tracking
8. Nutrient feedback
9. Activity tracking
10. Social support
11. Personalizing content to user profiles and intake history

However, both the focus group review and the initial study on the avatar concepts indicated that large portions of engagement and motivation depend on the serious game(s) provided within the platform. We thus start a new design cycle on a serious game for healthy nutrition. Again we should cover the requirements derived during the rigor cycle in chapter 2:

1. Use of mobile technology
2. Providing accurate nutritional information
3. Explaining provided feedback to enhance trust and empowerment
4. Conducting evaluations in real-life settings

Work on serious, persuasive, and positive gaming has already been reviewed in chapter 3 with a focus on frequently used design elements relevant to the platform design. The following section discusses additional resources focussing on the aspect of game-based interventions for health and nutrition and its effects on knowledge, motivation, and behavior change. While many different game concepts were designed and implemented, only the *Fit Food Fun* game was selected for iterative evaluations and improvements. The design iterations are discussed below.

5.2 RELATED WORK

As discussed in our rigor cycle (chapter 2), school-based interventions are a common tool for nutrition interventions in children and adolescents. One more recently upcoming way of providing these interventions is the use of games or computer-based serious games. We discuss the positive effects and drawbacks of three examples of health-related games: Kaledo, Pokémon Go, and Alien Health. The Kaledo game is a board game (Viggiano et al., 2015), but could easily also be provided as a computer-based variant. The game's core idea is to give each player a personalized contingent of calories, which they must fill with energy intake, represented by nutrition cards, and energy expenditure, represented by physical activity cards. After 15-30 minutes of gameplay, the player with the least difference between EI and EE wins the game. To win the game, players should gain implicit knowledge of both energy contained in food items and energy spent during physical activity. An initial study with 241 subjects (Viggiano et al., 2015) showed positive effects on nutrition knowledge gain and vegetable intake compared to the control group. These results were confirmed with 3110 subjects from 9-19 years. Even the follow-ups after 6 and 18 months showed significantly lower BMI-z scores for the intervention group. A mobile game that has changed the perception of digital gameplay to increase physical activity is Pokémon Go. Howe et al. (Howe et al., 2016) conducted a study on the number of steps taken in the first six weeks after installing the game via Amazon Mechanical Turk. In their analysis, they show an increase in steps after the first week of gameplay. However, this effect attenuates until the sixth week. Although their study sample of 1182 was quite high, their target group of age 18 to 35 years with an iPhone 6 may not be representative of interventions on children and young adults. A serious game for healthy nutrition is "Alien Health" (Hermans et al., 2018). The goal in this game is to feed an alien with various dishes to make it fit enough to save dying planets. For each food choice between two items, praise, feedback, and knowledge about nutrition facts are conveyed. In a study comparing this game to an active control group, the Alien Health game resulted in higher nutrition knowledge gain shortly after playing the game. However, at a two week follow up, the participants showed no significant difference to the control group anymore. This short-livedness indicates a further need to either design for persistent knowledge gain, or to provide the (game) intervention continuously over a longer time. Also, no effect on dietary behavior was visible. The persistence of knowledge and impact on behavior change when using the system for a long time have not been assessed yet. Repetition may help in retaining the gained knowledge. On the other hand, the retention of knowledge depends on the activation of connections to prior knowledge. This process could be impaired by a strong abstracting of the game world from real-life situations.

Besides studies on specific games that might give insight into the design and its advantages or disadvantages, a number of papers study the overall effect of gaming based nutrition and health interventions. An early work by Blakely et al. (Blakely et al., 2009) compared 16 empirical studies of gaming against traditional teaching. The authors conclude that both methods increase knowledge with similar effectiveness. However, they see indications that games enhance enjoyment and may thus improve long-term retention. The authors caution that success highly depends on the specific game and should be investigated carefully in each case. In 2015, Dudley et al. (Dudley et al., 2015) conducted another analysis, more specific to primary school children and healthy eating, and more generally regarding the teaching methods. The survey focused on four different healthy eating effects: reduced energy intake, increased fruit and vegetable intake, reduced sugar consumption, and improved nutritional knowledge. Overall the authors identified 49 original studies fitting these criteria with 29 targeting enhanced curriculums, 11 providing cross-curricular approaches, 10 including parental involvement, 10 on experiential learning, 7 reward or incentive-based reinforcements, 3 literature-based methods, 2 games, and 2 web-based tools. Dudley et al. find the largest effects for reduced intake, increased fruit and vegetable intake, and increased knowledge when using experiential interventions, such as cooking or gardening in class. Overall the authors conclude that school-based teaching interventions lead to positive changes in healthy eating behavior. One recent work specifically on games for healthy nutrition for children was conducted in 2019 by Chow et al. (Chow et al., 2019). The analyzed 43 original studies mostly focused on either increasing fruit and vegetable intake, modifying snacking behavior, encouraging food exploration, or general promotion of healthy eating. The authors find positive effects for all but the snacking behavior targets and further see three general advantages of game-based approaches, which are cost-effectiveness and scalability, seamless integration within or outside of the curriculum, and consistent content for all participants. Despite the benefits shown in their work, the authors see this research area at a very early stage with effects only proven for short-term evaluation and no assessment or reproducibility for unique game design elements.

To get more insights into the mentioned gaming elements, we want to discuss the extensive body of research on serious games for health by Tom Baranowski et al. In their early work (Baranowski et al., 2008b), they analyzed 25 video games that promote healthy behavior. The authors conclude that most of the research shows positive behavior changes, but caution that this success cannot be linked back to specific mechanisms and gaming elements. The authors suggest further research on the optimal use of features such as storytelling, interactivity, and behavior change technology. In 2011 they published a randomized controlled trial on the games "Escape from Diab" (Diab) and "Nanoswarm: Invasion from Inner Space" (Nano) (Baranowski et al., 2011) with 133 children between 10 and 12 years. The authors did extensive outcome measurements of dietary intake, physical activity, and phenotypic data. While they show moderate effects with an increase of 0.67 servings of fruit and vegetables per day (5 is recommended), they did not show effects on water consumption, physical activity, or body composition. To improve the design and development of new games for health, Baranowski et al. published a guideline report in 2013 (Baranowski et al., 2013). The authors promote a strong connection with behavior theory suggest mediators (e.g., self-efficacy) that guide the design by their causal relation to both the intervention techniques (actions theory) and the behavior change outcome (conceptual theory). After choosing appropriate theoretical strategies, Baranowski et al. suggest adapting existing research on such mediators and theories to the specific problem. MacKinnon et al. (MacKinnon, 2011) elaborate on how such mediators could be integrated into research design, by predefining a logical connection based on theory and measuring those connections in both intervention and control conditions. Finally, Baranowski et al. (Baranowski et al., 2013) note that there is little research on the maintenance of behavior change through games for health in children. Mechanisms indicated to be successful among adults are enhancing basic psychological needs (e.g., autonomy, competence, relatedness) or personal relevance via storytelling and characters. Baranowski et al. further elaborate and emphasize important concepts for games for health, such as game mechanics, storytelling, challenges, feedback, incentives, goal-setting (real-life), and tailoring. Baranowski et al. further elaborate and emphasize important concepts for games for health, such as game mechanics, storytelling, challenges, feedback, incentives, goal-setting (real-life), and tailoring. The authors explain that storytelling might increase identification with a character and improve acceptance of health-related content and behavior transmitted by the character. However, they note that the effectiveness of storytelling for behavior changes is still unclear. On the other hand, challenges can lead to enjoyment or even flow states, if their difficulty and its increase over time are adequately adapted to the user. While the motivating effect of feedback in various forms it clear, its effective implementation still requires further research. Even for the general gaming context, many dependencies of this component, such as users' social classes with the reaction to negative feedback, are still unknown. These dependencies may even be more influential in the very personal context of health behavior. The role of incentives in behavior change is also ambiguous, with participants discontinuing incentivized behavior after the intervention due to a replacement of intrinsic motivators with the given incentives. Instead, addressing intrinsic needs such as autonomy, competence, and relatedness or giving meaningful social rewards can help sustain changes. Goal-setting has been very successful concerning behavior changes since it can extrapolate the game world's content into real life. Finally, tailoring content such as these goals to the user has been repeatedly successful in changing behavior. However, additional input from the users is usually necessary to be able to provide such tailoring.

In 2014 (DeSmet et al., 2014), the authors extended their recommendations by conducting a meta-analysis on the health-promoting effects of serious games. The authors include 54 serious digital game studies for a healthy lifestyle and show small positive effects on a healthy lifestyle and its determinants, especially knowledge, and very small effects for clinical outcomes. While effects in, e.g., knowledge, were maintained in the long-term, the behavior was not. The authors reconfirm a positive influence of having strong theoretical foundations regarding behavior theory and game design. The authors summarize the strength of the assessed games in terms of their universal appeal across populations, and their flexibility to be integrated into diverse programs. The strongest limitation of the analyzed research is the heterogeneity of effects and the ambiguity of missing effects due to underpowered studies. Their following report in 2016 (Institute of Digital Media and Child Development Working Group on Games for Health et al., 2016) focusses more specifically on the target group of children. As indicated in their prior work, the authors emphasize the lack of empirical results on the effects and adverse effects of different game designs and behavior change procedures. The authors conclude that substantial, high-quality research and appropriate funding are necessary to understand the impact of mediators and moderators in games for health. The involvement of a variety of different stakeholders is needed to reach the appropriate effectiveness and use of these games. Most recently, Baranowski et al. published two more summaries relevant to this work. The first one (Baranowski et al., 2019b) analyzes 22 publications on games for nutrition education and dietary behavior change. The authors conclude that while most studies report positive effects, the quality of research is rather low, and the scope of actual results is limited and inconsistent. The second one (Baranowski et al., 2019a) gives guidelines for strengthening the criticized research base and systematically improving the knowledge of effective games for health. The authors emphasize a focus on promising effects of gameplay and on understanding relevant mediators across any health behavior and target group.

5.3 Initial Design and Selection of the Serious Game

The initial design and implementation of the *Fit Food Fun* game were developed in two iterations by (Struzek, 2015,Ziegltrum, 2017), supervised by my colleague David Plecher. The following section describes the initial design and discusses the reasons for choosing it over other prototypes in the review by our *enable* nutrition experts.

5.3.1 *Design Requirements and Refinements*

The core nutritional concepts conveyed in the initial prototype by Adrian Struzek (Struzek, 2015) are the ten rules of the DGE (Jungvogel et al., 2013) and the nutritional content of food items based on e.g. the USDA food database (EuroFIR, 2020). The storyline portraits groups of food hunters that travel through Europe to collect new ingredients for their dishes. The single levels are designed as 2D platform games with obstacles to overcome, and quizzes or puzzles to solve for proceeding. Each level is a short gameplay of 8 minutes representing one day-cycle in the game world. Players have to pack their backpack with three meals from a list of food items for each level. The meals can be used to refill energy during the level. The quizzes and puzzles contain either question on food items, or calorie estimation puzzles, or card games between different food items. The energy amount spent on each level is based on the MET scores of activities done during the game and a default player weight of 50 kg. The energy provided by the backpack is constrained by available food items in the current region leading to new estimation challenges for each run. Figure 15 shows the initial Europe map, the design of a food item for the card game, and the design of the backpack.

Figure 15: Map of Europe, food item info card, and backpack for food collection. These figures have been taken from (Struzek, 2015).

The initial design and concept of the *Fit Food Fun* game were further refined and implemented in the master's thesis of Johannes Ziegltrum (Ziegltrum, 2017). Two substantial changes concerning the nutritional content were a switch to the Bundeslebensmittelschlüssel (BLS) (Hartmann et al., 2005) for nutritional information on food items, and the explicit integration of the ten DGE rules during the loading screens of each level (figure 16, right). Concerning the game concept, a significant change is the disentanglement of quizzes and puzzles from the backpack running game. Each country now offers three mini-games (figure 16) with the available food items based on the current country context. The first mini-game (figure 16, left) takes the idea of the food item card game and lets the user choose the highest bidding food item for different macro-nutrients and the calorie amount. Each level consists of 20 card comparisons. This game aims to give the players a sense of the relation between different everyday food items. The second mini-game (figure 16, middle) takes the idea of the calorie estimation game and extends it to covering important nutrients for weight gain, such as fat and sugar. The amount is shown as sugar dices and fat drops. When the estimated amount is wrong, arrows indicate the direction of over- or underestimation, and the user can try again. The game is limited to 10 tries and gives points for every correctly estimated food item. Finally, the third mini-game (figure 16, right) is based on the original backpack running game. For each round of running, swimming, and cycling, the user can fill five slots in the backpack with food items. The energy expenditure is still based on MET scores. The duration of the exercise is assigned randomly for each level. After the mini-game is passed, a summary of energy spent and packed is shown, including the distribution of macro-nutrients. In addition to the three mini-games, the overarching storyline of exploring Europe is enhanced by a three-star system for each level and each country. Rankings of players support social motivation. Finally, coins collected in mini-game three can be exchanged for healthy recipes.

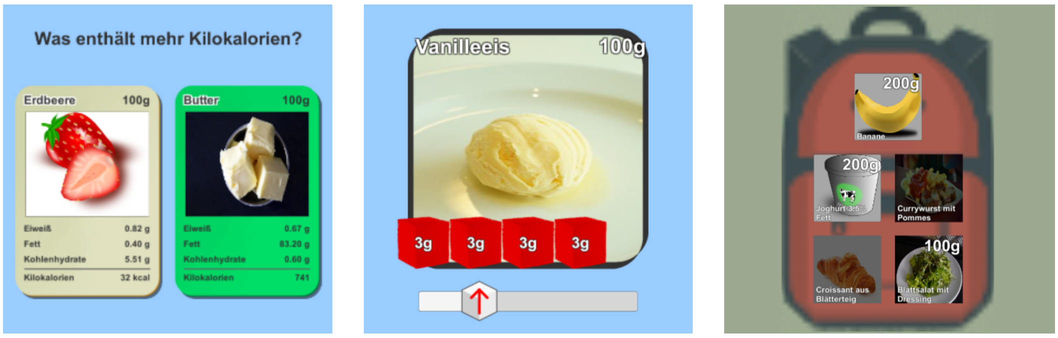


Figure 16: Mini-game 1 consisting of card choice, mini-game 2 consisting of estimation challenges, and mini-game 3 with a new graphic design. These figures have been taken from (Ziegltrum, 2017).

5.3.2 *Evaluation Method*

Four additional game prototypes were created parallel to the *Fit Food Fun* prototype under the supervision of my colleague David Plecher. One system comprises an ISS game where astronauts had to choose their food for group adventures (see also (Rösler, 2017, Mitschenko, 2017)). Another system comprises an RPG game designed to bring players outdoors for collecting food items, similar to Pokémon Go (see also (Soyer, 2017, Neumann, 2017)). A Tamagotchi like game based on the avatar from the central platform was developed in three iterations (see also (Le, 2016, Mück, 2017, Böker, 2018)). One game design with real-life social interactions during joint cooking events was designed and revised in two iterations (see also (Mayer, 2017), (Barounig et al., 2017)). Two expert colleagues from nutrition medicine evaluated all prototypes for potential nutritional knowledge they could convey to children and their feasibility for a school-based intervention.

5.3.3 *Results*

There were several unique characteristics of the *Fit Food Fun* game that resulted in its choice as the main serious game to be refined and evaluated. Compared to the *Fit Food Fun* storyline, the ISS concept of nutrition in space was too estranged from any real-life situation. *Fit Food Fun* delivers a transferable set of food items in different countries and energy expenditure during running, swimming, and cycling. In contrast, the energy expenditure measures in space and the food items available were not an optimal storyline for transfer knowledge. This choice represents a balancing act between different goals of a serious game for healthy nutrition. While a more creative and inspiring setting, such as in the ISS game, might be more motivating to play the game, the more realistic setting is more prone to impart knowledge connected to real-life situations. The RPG outdoor game was considered attractive in terms of physical activity support, but the primary interaction was not sufficiently connected to nutritional education. During the expert review, the group cooking event was considered very beneficial from a social motivation perspective and concerning knowledge-transfer to real behavior. However, the intervention would require groups of friends with access to cooking environments. On the other hand, the *Fit Food Fun* game could be evaluated with minimal pre-requirements in a school-based setting. Finally, the Tamagotchi game raised psychological concerns. Two design options were either realistic effects of food consumption, which would be minimal on short-term or exaggerated reactions such as the avatar's immediate weight gain. The first option might not motivate players from a design perspective, and the second might raise too much fear of overeating in children. Besides the limitations of the other games, the *Fit Food Fun* game was exceptionally well regarded for its integration of multiple DGE rules, for its realistic and education context on the European map, and its connection to physical activity. Additionally, the short duration of single levels reduces the overall screen time introduced by the game and enables casual gameplay during travel time or school breaks.

5.4 IMPROVEMENT AND EVALUATION OF THE PEDAGOGICAL COMPONENT

For the first major revision of the *Fit Food Fun* game, we conducted a systematic review and refinement of the gameplay according to different serious game methods and pedagogical models (see also (Brandl, 2017)). This chapter elaborates on the most significant changes and the results from the first evaluation of the resulting prototype.

5.4.1 *Design Requirements and Refinements*

As a first step, the *Fit Food Fun* game was analyzed for its coverage of important game elements as provided by the book of Kapp (Kapp, 2012), and game mechanics as summarized by Dadaczynski et al. (Dadaczynski et al., 2016). Both categorizations are mostly covered In the *Fit Food Fun* prototype. Extensions in this cycle of refinement were the addition of a specific route through Europe, where new countries are only revealed after the previous ones are mastered, and the addition of golden countries once all levels are perfectly mastered. Furthermore, mechanics that were already implemented should be improved, such as the selection of food items and the difficulty and point balance of levels. The two pedagogical models that were analyzed and applied in the *Fit Food Fun* game are the AVIVA model (Städeli, 2013) and the ARCS model (Keller, 2009). The AVIVA model is built on five phases of education:

1. Arrival
2. Repetition
3. Information
4. Processing
5. Evaluation

These were integrated into the *Fit Food Fun* game as follows: The arrival phase is additionally supported by an introduction game, where food item cards can be viewed for each country without further necessary actions. The repetition phase is supported by including food items from previous countries into the following country's games. The information phase is provided by the card game and estimation game. The processing phase allows the in-depth application of previously learned information. This phase is provided by the backpack game. Additionally, this cycle between information and processing is implemented over the progress through countries by switching from weight-based comparisons to portion-based comparisons to deepen knowledge applicability and increase the challenge. The evaluation phase is provided by the three different stars depending on the performance during the game. The ARCS model requires four components:

1. Attention
2. Relevance
3. Confidence
4. Satisfaction

These were integrated into the *Fit Food Fun* game as follows: The attention component is provided by stepwise revealing new food items and the increasing difficulty of countries. The relevance component is provided by allowing individual exploration of the travel route. The confidence component is supported by transparent evaluation criteria and slowly increasing difficulty. The satisfaction component is provided by positive feedback messages independent of the actual game outcome. In addition to reviewing and updating the game mechanics, changes to the nutritional content were conducted in this refinement. The food items were coherently colored by their food groups to allow transfer and further implicit learning (figure 17). The selection of food items per country was adapted to cover two of each category. Finally, the level-balancing of all games was revised.

5.4.2 *Evaluation Method*

After revising the prototype, a first evaluation of the systems was conducted with 10 participants over a time frame of 45-70 minutes each. Each participant could test the application using a think-aloud method, was questioned in a semi-structured interview, and had to fill in a questionnaire including a System Usability Scale (SUS) (Brooke et al., 1996) assessment. One goal of the interview was to understand the participants' attitude towards nutrition and their previous knowledge. Thus, we included questions about nutrition information retrieval, dietary behavior, intention, and attitude towards healthy eating and plans of changing one's current diet. The goal of the questionnaire was to test the knowledge of nutrition before and after testing the game. The five knowledge areas that are tested are:

1. Energy requirements
2. Energy expenditure during physical activity
3. The sugar content of food items
4. The calorie content of food items
5. The fat content of food items

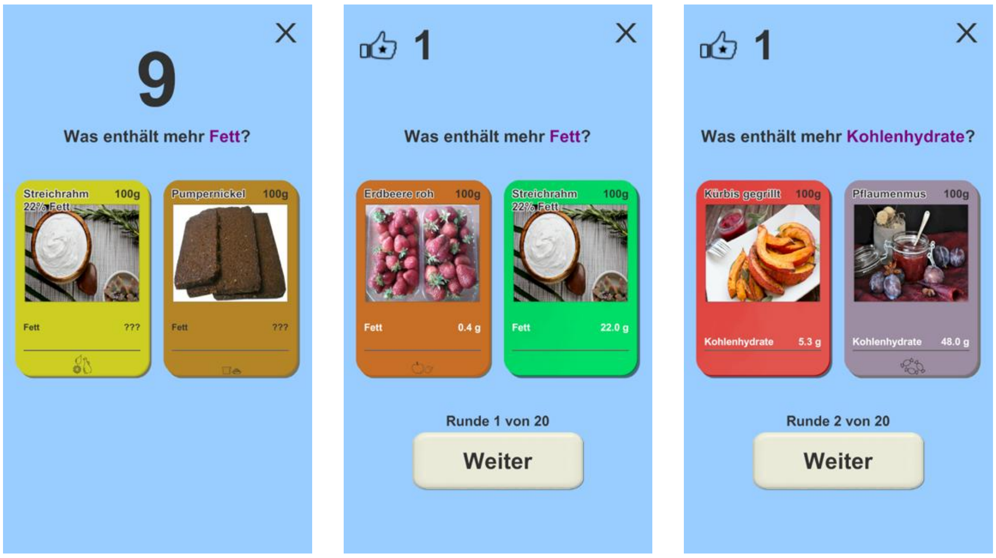


Figure 17: Mini-game 1 gives a choice of two food items and a targeted nutrient. In the beginning, cards are colored by their food category in the BLS. When one card is selected, it turns either green (correct) or red (incorrect).

6. The categorization of food items by their food group

During the game test, participants could explore freely while solving four tasks and telling their thoughts to the moderator. The tasks are:

1. Get an overview of the application
2. Play each mini-game
3. Unlock a new country
4. Collect three gold stars in one country

5.4.3 *Results*

The ten participants in the study were students between 19 and 27 years. The interview gave interesting insights into the nutrition attitude of the participants. Most frequent sources of nutrition information are the media and family members. Participates mostly cook on their own and only a few regularly eat at the university canteen. A part of the participants view eating as a reward, and others try to stick to a diet. Almost all participants drink sufficiently and try to avoid soft drinks. The concept of a bad conscience was mentioned about eating fast-food, sweets, chips, or cake. These responses indicate a basic level of understanding regarding healthy nutrition. Part of the participants state intentions for a better diet, including eating more self-cooked food, eating healthier, eating more vegetables, and eating less fast food. Other changes that were mentioned are eating more regularly and more diverse. The nutritional knowledge ranged from 30% to 80% of correct answers. In the post-questionnaire, this knowledge increased by up to 25% for seven participants and decreased for three participants. This positive change indicates that the game is transferring knowledge. However, as seen in the three negative change cases, this transfer is not working for all participants. The SUS score resulted in an average of 64.75, which indicates that the system is still in a prototypical state but already more usable than e.g., 46.7 for MyDietCoach (Ferrara et al., 2019). Positive aspects mentioned about the game were the animations and interactions, the golden county reward, and the graphical representation of food items. Mixed feedback was given regarding each game's learnability, the color palette, and the difficulty of the levels.

5.5 Improvement and Evaluation of the Nutritional Component

In the second major revision of the *Fit Food Fun* game, we refined the nutritional content provided within the game and helped in the execution and evaluation of multiple focus groups on the *Fit Food Fun* game (see also (Weber, 2018)). This section discusses the most significant changes and the results from the evaluation of the resulting prototype.

5.5.1 *Design Requirements and Refinements*

Figure 18: In the map of Europe, each country is shown with a color-coding (red=locked, green=all games passed, gold=all games have a gold star). If the green and golden countries are be opened their flag, and the three mini-games with their currently highest number of reached stars are shown. The DGE screen is shown while loading one of the three mini-games. After finishing the mini-game, the points and stars are calculated and shown.

As a first step, the game's usability was adapted according to the previous evaluation results, especially on the missing explanatory texts and graphical quality. Figure 18 shows the changes targeted at decluttering the interface of both single countries and the overall Europe map. The collection of coins in game three and the corresponding recipe shop were replaced by a food lexicon, which now provides the introductory content in the form of nutritional information without the game pressure. The user profiles and rankings were hidden since the system is evaluated separated from the platform. The graphical design was revised. For example, buttons were redesigned, icons were enlarged, and the national flag replaced the neon-green color scheme in each country.

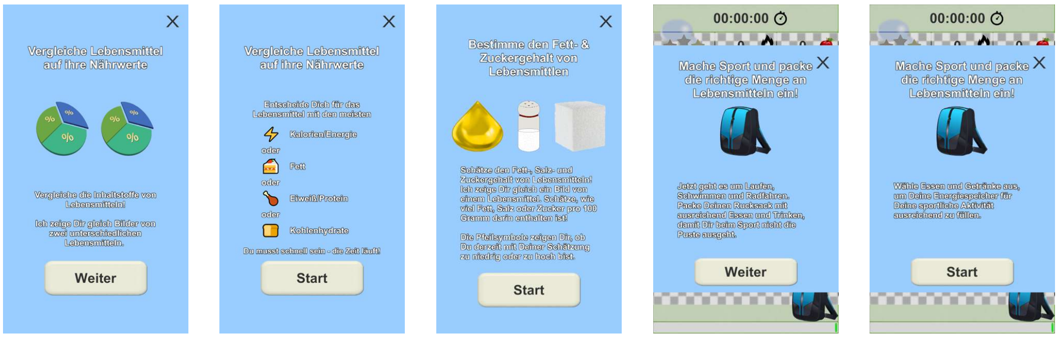


Figure 19: Revised introduction screens giving an explanation of the game mechanics for mini-game 1 (left two), mini-game 2 (middle) and mini-game 3 (right two).

All introductory texts were revised to better explain the games content and goals. The texts were further enriched with nutritional information provided by the domain experts. Additionally, the texts were revised to fit the younger audience of the game and supported by graphical elements. All introduction texts are visible in figure 19. Further design changes were conducted in each mini-game by e.g. highlighting currently focused nutrients in the card game, and correct answers after the time is over.

Figure 20: In addition to the games, the food lexicon provides all nutritional information of the food items sorted by their country. This way, players can train and learn before challenging levels.

Besides the usability adaption, the nutritional content was revised together with experts from nutrition medicine. Out of the ten rules, only six were selected to be represented in the game both in textual form on the loading screens and implicitly in the mini-games. We could not include the rule about eating diverse because we do not give individual food items any context in the game. We also could not include the rule about animal-based and plant-based food items, since this is not represented in the nutritional database, we are using. Finally, we considered the rules about cooking gently and taking time for meals to be mainly controlled by parents and thus did

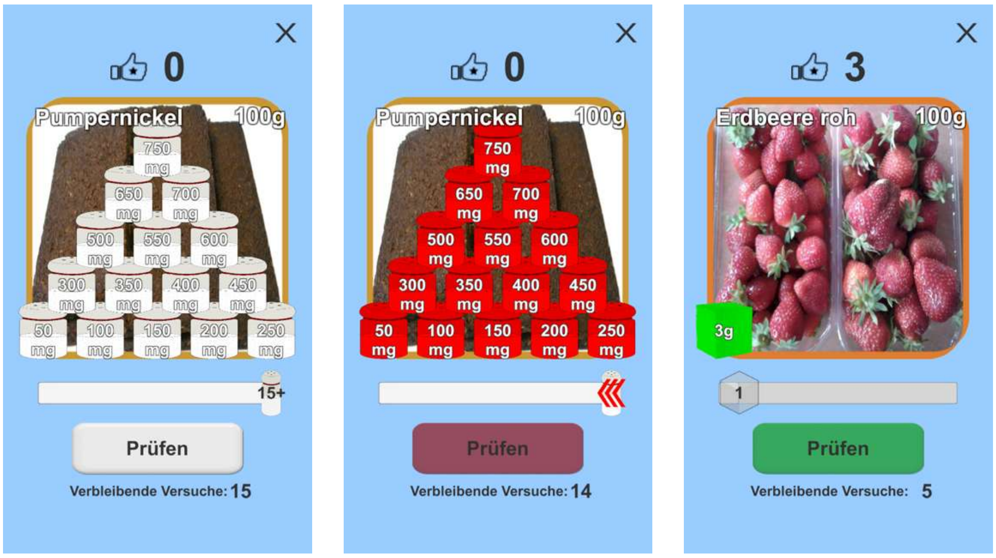


Figure 21: We changed mini-game 2 to include salt and to give hints, in the form of 1-3 small red arrows, on the direction and strength of errors in the estimate.

not exclude them either. The textual representations were shortened and adapted to the language of the target group. Instead of randomizing them, they are shown to ensure similar coverage of each rule for all users. Within the games are included in the following way. Mini-game 1 implicitly covers the advantages of whole wheat products. Mini-game 2 covers the two rules on reducing sugar and fat and is extended to include salt in this refinement (figure 21). Mini-game 3 primarily focusses on the rule about physical activity and is extended to include the collection of at least five fruits and the coverage of water during each activity, to cover two more rules.

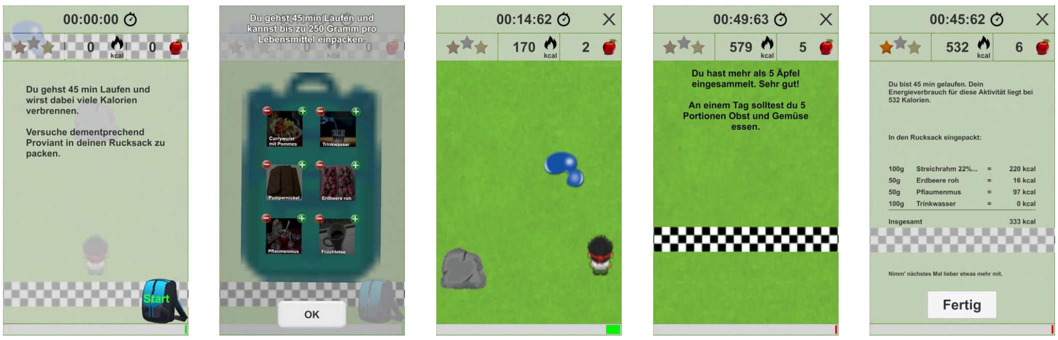


Figure 22: Changes to mini-game 3 include the addition of water to the backpack, feedback on collected apples, and feedback on the caloric balance between the exercise and the packed food.

The largest nutritional modeling changes were done to the physical activity game (figure 22). The game design was changed to a fixed time of running, swimming, and cycling, allowing the model to use MET scores for each of these activities and to precompute the energy expenditure. The time intervals available are 30, 45, and 60 minutes, to give realistic examples for the target group. The race distance is computed for these times with the speed given in the MET description. The calories are calculated by multiplying the MET score with the user's weight and the time in hours. The weight is included in the user profile. The game is thus personalized to each player. The precomputation further enables a timer view with one minute per second passing. A bar at the bottom shows the calories left in the backpack. The time spent and thus the calories burned are increased when running through water or hitting stones. Thus, the players can improve their score with purposely running longer if they packed too much food. The evaluation is not based on time anymore, but on the matching between calories burned and packed.

Finally, each level's difficulty was revised, and the selection of food items for the first two mini-games based on reasonable nutritional values. The maximal amount per food item in mini-game 3 was set to 250g with five steps of 50g. Additionally, the calorie content is now visible in the backpack to ease the selection. The selection of food items for each country was conducted by nutrition experts to cover each food group's representative items. In mini-game 3, the food options are limited to one meal item, one fruit item, one sweets item, one drink, and water.

5.5.2 *Evaluation Method*

The second evaluation aims to retrieve the opinions and perceptions of the actual target group compared to the student participants in the previous evaluations. To reach this target group, the three focus groups were conducted in a middle school in Rosenheim, Bavaria. Participation is by choice and with parental consent. All participants were between 12 and 17 years old. The focus group lasted for two 45-minute lectures, with a 5-minute break in between the sessions. The research questions targeted were whether *Fit Food Fun* provides motivation and knowledge gain and how it could further be improved. Every focus group started with introducing the project, the team, and the methods used during the session. All comments were protocolled and recorded twice to ensure the feedback is captured. The questions followed a strict guideline with approximate timings for each topic to ensure the comparability of the groups. The first topic covers general questions on nutrition and digital gaming to get to know the participants. Afterward, a trailer of the game was shown to everyone, and their first impressions are collected. After the break, all participants could play the game for 15 minutes. The last part of the discussion collected feedback about the gaming experience and design. All participants received a small gift (healthy sweets) as a token of appreciation. The first group consisted of four male participants aged 14-15 years from the 8th grade. The second group consisted of three participants with one female and an age group of 15-17 from the 9th grade. The third group consisted of six participants with two females and an age group of 12-14 from the 7th grade. The youngest participant group showed the highest motivation and engagement during the study.

5.5.3 *Results*

The protocols and audio recording of all three focus groups have been analyzed by categorizing them into deductively predefined topics. The main categories are comments on the target group, their motivation, their knowledge gain, and their design perception. All main categories were inductively divided into subcategories based on the content of the discussion. The questions regarding the target group indicated that most participants are aware of their nutrition and, in a few cases, even looked up nutritional values of, e.g., drinks beforehand. While the participants frequently use their smartphone, only five participants regularly play games, and five others casually play games. Regardless of their current habits, all participants were positive about playing a game on nutrition. The second main category is focused on how the game support motivation. One subcategory that was mentioned multiple times is the level of difficulty within the different levels. While a number of participants had problems with mastering the games under the given time and trial constraints, especially in the estimation game, others were worried that they would get too practiced after a few runs and thus not play the game anymore. Another topic of discussion was the game design. The graphical elements were criticized, especially in the backpack game. Finally, the amount of text was mentioned as demotivating and frustrating. Overall the repetitiveness of mini-games in each country was viewed as boring. About half of the wishes named for a nutrition game are already fulfilled in *Fit Food Fun*. After seeing the trailer, nine of the thirteen participants state that they would play the game, and eleven would recommend it to friends or family members. Regarding the timing and duration of gameplay, most participants would causally play the game during waiting times or travel. Others would stop playing the game once they had reached every country once. During the discussion, the game was seen more as a means of learning about nutrition than as entertainment. The backpack game was the favorite mini-game followed by the card game. Another motivating aspect of the game was the Europe storyline. The third main category of knowledge gain was difficult to estimate due to the short testing phase. A part of the players showed a minimal gain in knowledge, but mostly in implicit ideas such as the surprisingly high amounts of fat and sugar in specific food items. A part of the players stated that they were too focused on game mechanics to remember the nutritional details. The final category of wishes and improvements is already partially covered by the critical points of the motivation category: less text, nicer graphics, more interactivity, the difficulty of estimation game, and unclear task in the backpack game. Beyond that, participants wished for background music, additional challenges, low data-rate usage, and social or multiplayer interactions.

5.6 Improvement and Evaluation of Usability

Based on the same focus groups as used to evaluate the effects of the *Fit Food Fun* game on motivation and knowledge, a second analysis was conducted by Liou Bao(Bao, 2018) concerning the usability improvements and technical issues. These were improved as far as possible, given the time constraint of the upcoming pilot study. After these refinements, a usability study was conducted (see also (Borchers, 2018)). This chapter elaborates on the most significant changes and the results from the evaluation of the resulting prototype.

5.6.1 *Design Requirements and Refinements*

The secondary analysis of the focus group results leads to a list of overall improvements, specific usability improvements, and technical issues. The overall improvements suggested were updating graphics, increasing difficulty with advancing levels, adding more variety to the mini-games, adding multiplayer functionality, reducing text, adding background music, and providing offline gameplay. The usability improvements were focussed on specific parts of the gameplay. A part of the players did not note the food lexicon and thus would like a hint about this cheat sheet. Some players also did not realize that the new country was available, once they completed all three levels in the first country. Both information shortages could be solved with notifications. In mini-game 1, the only issue was the shortage of time and, thus, the game's difficulty. This issue was contrasted by other players who found the game to be easy. Mini-game 2 had the most critical feedback. Many players did not realize the arrows that were giving them hints to improve their estimate. Also, the players coherently reported that there were not enough trials offered to solve the game quickly. To most popular and thus most discussed game was mini-game 3. The apples introduced to the game to represent another DGE rule were mostly dismissed as boring since they were not connected to the overall game success. Some players had difficulties controlling the avatar during the running session and complained about too slow reaction times. During the backpack selection, some players did not understand how to remove and increase ingredients. A revised introductory text could improve some of these issues. Not all the suggested usability improvements could be incorporated until the pilot study of the game. Changes that were conducted are: increase the number of trials in the estimation game, increase the time limit in the card game, add buttons for removing and adding food items to the backpack, and localizing images to reduce data traffic. Changes that were not possible are: giving a tutorial for the game, revising graphics and sounds, reducing important texts, additional mini-games, and multiplayer mode. Besides the changes derived from the focus groups, other changes were necessary to facilitate the upcoming pilot study. Instead of a tutorial, the game was improved by an introductory text explaining the game's overall storyline. Additionally, the personalization of physical activity metrics and the logging of interactions required a dedicated user profile for each study participant. Finally, due to the limited amount of available devices, user accounts need to be exchanged between sessions in the pilot study without losing any logging or profile data. Before the pilot study, this final prototype was evaluated in a user test discussed in the subsequent section (see also (Borchers, 2018)).

5.6.2 *Evaluation Method*

The goal of the evaluation is to test the usability of the final prototype in several scenarios. The usability test was completed by five participants with a duration of 50 minutes for each session. After a short introduction into the project and the schedule, general data was collected on the participant, such as age, gender, nutritional attitude, and smartphone usage. The main session of gameplay was planned to last 25 minutes and guided by nine scenarios. During the test-phase, both audio and screen were recorded, and the participants encouraged to communicate their thoughts according to the think-aloud concept. The scenarios were covering all of the application features but left room for exploration and individual solutions:

1. Login
2. Play mini-game 1
3. Reach one star in the estimation game
4. Find the number of carbs in plums
5. Play the backpack game and collect at least six apples
6. State the number of calories burned for which activity and time plus the packed calories
7. Find the amount of fat in 100g of white sausage
8. Find the number of carbs in 100g of croissant (hint to France)
9. Logout

After conducting the test with all scenarios completed, the users received three questionnaires to complete. The SUS questionnaire (Brooke et al., 1996) and the User Experience Questionnaire (UEQ) (Schrepp et al., 2014) were used to assess usability. The third questionnaire contained the questions from the focus group interview guide to allow a comparison to previous results.

5.6.3 *Results*

The study was completed by five participants aged between 20 and 53 years. Two participants were female, and four participants estimated their nutritional knowledge to be good. Concerning healthy nutrition behavior, only 60% gave positive feedback. Most participants stated to spend 4-5 hours per day on their mobile phones. During the test phase, the completion of scenarios was evaluated by their success, their timing, and possible usability issues that were mentioned during the think-aloud part. Almost all situations were solved when giving hints once the player gets stuck. Most of these hints were necessary for finding nutritional information on a specific food item. The timings strongly varied by users dependent on how much they communicated during the test and how many hints they required to solve the tasks. On average, the scenarios took between one and five minutes, depending on their mission. Smaller usability issues detected in the audio recordings are: nutrient category of estimation game is not written explicitly, food lexicon was not used, the maximum amount for packing the backpack was unclear, and the login button needed to be clicked twice. The SUS evaluation resulted in an average score of 79, with 75.8 for usability and 92.5 for learnability. This score is a definite improvement against the initial usability test with an average SUS score of 64.75. The UEQ resulted in average positive ratings with the best ratings given for transparency, efficiency, and controllability. The focus group questions showed that four of the five participants liked the game and did not see significant usability issues. In contrast to the focus groups, graphical elements were perceived positively. However, the lack of sound was criticized again. Overall the evaluation shows that the game is ready to be used by children in a real-life setting.

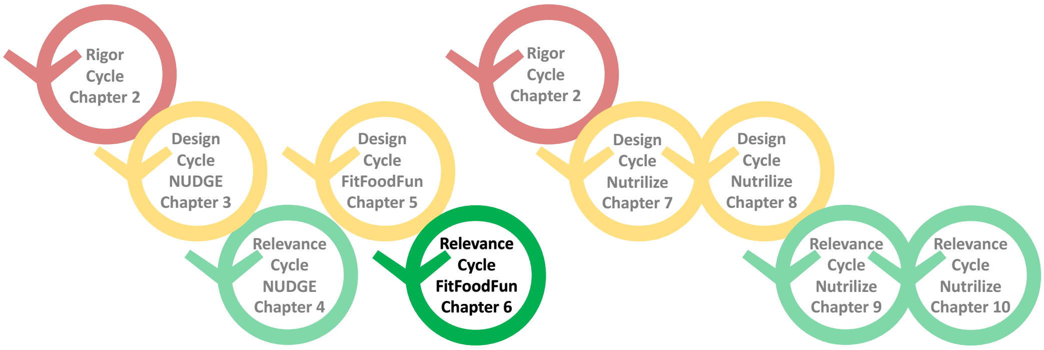
5.7 CONCLUSION AND NEXT STEPS

This chapter has covered the first design cycle of the *Fit Food Fun* game, including the derivation of requirements compared to the *NUDGE* platform from the rigor cycle, focus groups on the effects and usability of the prototype, and user tests for the first and last iteration of the prototype. In the next chapter, we discuss evaluating this final prototype concerning its effects on children in a real-life pilot study. The results of this evaluation are the focus topic in the subsequent chapter.

The *Fit Food Fun* serious game for healthy eating designed in this second design cycle was perceived well by the targeted group of children between 14 and 17 years. The main insights gained from the focus groups are limitations of the graphical design, concern about boredom after playing the games for a longer duration, and a clear tendency of older participants to be less enthusiastic about the design. The main insights gained from the final evaluation iteration is that the game provides sufficient usability and understandability to be played outside a moderated laboratory context. The subsequent chapter focuses on the *Fit Food Fun* serious game in a real-life context and especially targets an understanding of users' interactions with the game over a longer duration. In this second relevance cycle, we evaluate the effects of the *Fit Food Fun* game compared to traditional teaching methods.

6

PILOT STUDY ON A SERIOUS NUTRITION GAME



After iteratively improving the *Fit Food Fun* game in our design cycle, we conduct a large scale study on the effects of playing the game on the target group. We want to see our artifact's impact and limitations in a real-life setting during this relevance cycle. The study's goal is to show the difference in impact between playing our serious game and classical teaching. Further, we analyze how the game influences knowledge, attitude, and behavior. The pilot study was conducted in two middle schools in Rosenheim. In one school, the participants had to play the *Fit Food Fun* game for three 15-minute sessions, each on a separate consecutive day. In the other school, a control group received lectures on the nutrition knowledge integrated into *Fit Food Fun*, for 15-minute sessions on three consecutive days. Parts of these results concerning the nutritional viewpoint have been published as a paper in the Nutrients Journal with me as the second author (Holzmann et al., 2019b). We discuss these results and move beyond the knowledge improvement to how the game elements transferred knowledge and motivation and how user characteristics and context variables interact with these effects. The mediating variables investigated are the previous knowledge, motivation, behavior, the users' characteristics, and the gaming or teaching experience. In line with the overarching research questions of this thesis, the study thus investigates the impact of the *Fit Food Fun* game on nutrition knowledge and motivation towards healthy eating.

6.1 MOTIVATION

Overweight, obesity, and unhealthy nutritional behavior are issues faced by many children worldwide (WHO, 2017a). As shown in the rigor cycle 2, many interventions targeted at improving children?s nutritional knowledge and behaviors are conducted in school settings. However, classical teaching does not scale for giving long-term support to children. As reviewed in the related work section of chapter 5, serious games can provide similar benefits as classical teaching and sometimes even provide long-term effects at follow-up assessments concerning nutritional knowledge

(DeSmet et al., 2014). As a pilot study for our developed *Fit, Food, Fun* game, we want to assess its success at departing nutritional knowledge compared to classical teaching. Additionally, we want to investigate the relevant mediators, as suggested by (Baranowski et al., 2019a), that lead to this knowledge gain. We especially want to compare these mediators with mediators relevant in the teaching context to gain further insights into potential best practices in building serious games for healthy nutrition. We also investigate the internal effects of the *Fit, Food, Fun* game elements on internal game success, which is one such potential mediator.

6.2 PROPOSED SOLUTION

This section summarizes the final version of the serious game *Fit Food Fun*. The section reviews the final product of the iterative design and evaluation process in chapter 5. Our game is designed as a culinary journey through Europe with challenges on different nutritional aspects represented by three mini-games. The journey and the educational content represented within the mini-games are designed according to the pedagogical models AVIVA (Städeli, 2013) and ARCS (Keller, 2009). The nutritional knowledge is based on the ten rules of the DGE (Jungvogel et al., 2013) regarding the promoted guidelines, the Bundeslebensmittelschlüssel (BLS) (Hartmann et al., 2005) regarding the nutritional information in individual food items, and the MET scores regarding the energy expenditure during physical activities. The following six of the ten DGE rules are represented both explicitly within the loading screens of each game and implicitly during the gameplay:

1. Take 5 of fruits and vegetables per day
2. Eat whole wheat
3. Eat healthy fats
4. Limit sugar and salt intake
5. Drink water
6. Be aware of body weight and stay physically active

Additionally, each country covers one food item of each DGE food group - cereal products, vegetables, fruit, milk products, animal products, fats, beverages - and one food item of each of the two additional BLS categories - meals, sweets. Each group has a color code to promote implicit learning effects on these groups. The selection of food items for each country of the journey is additionally adapted to contain culturally representative food items. This selection enhances the storytelling effect and provides additional knowledge to the users. Progress is represented by color-coding the countries in the map view in red (not unlocked), green (unlocked), and gold (all games won with gold star evaluation). Progress is further visible by the count of reached gold stars in the map view. An introductory explanation offers support for beginner players showing nutritional terms, textual display of the DGE rules on the loading screens, and a dictionary with the nutritional information of each country's food items. The actual gaming experience is offered via three different mini-games that are available in each country. The first mini-game is intended to teach about the macro-nutrients and calories contained in different food items. The core gaming mechanism is the comparison of two food items regarding one of the macro-nutrients. This comparison is conducted in 20 rounds and focusses on the ten food items offered in the current country plus the ten items of the previous country to allow for knowledge transfer. Each comparison must be made in 9 seconds in the first 12 rounds and 6 seconds in the final 8 rounds to challenge the user. After each comparison, the correct answer is revealed. The user has unrestricted time to read the correct selection and the underlying values for the macro-nutrients of the two food-items. At the end of the game, stars (bronze, silver, gold) are attributed according to the number of correct selections within the 20 rounds. The second mini-game focusses on the (hidden) content of fat, sugar, and salt in different food items. The core gaming mechanism is an estimation game where the player gets 15 trials to guess the correct amount by sliding between different numbers (cubes 3 g, drop 3 g, dashes 50 mg) for different food items shown on a picture. When guessing wrong, the game hints at the direction and distance of misestimating with small arrows on the slider. When guessing correctly, the next picture is shown. The success in stars is defined by the final number of correctly estimated food items. The third mini-game focusses on the calorie balance between consumed food items and conducted physical activity. The core gaming mechanism is the correct packaging of food for a specified physical activity. The activities cover running, biking, and swimming for 30, 45, or 60 minutes. The burned calories are estimated using the participant's weight and the MET scores for these activities. The backpack can be equipped from five of the country's food items in steps of 50g. The resulting calories for each food item are shown during the selection process. Additionally, the backpack can always be equipped with a bottle of water to support the DGE rule about drinking sufficiently without changing the calories included in the backpack. If the player does not include any drinks for the activity, a warning is shown. The physical activity is simulated in speedup (1 minute represented as 1 second). The player has the option to increase the overall calorie expenditure by running through mud or around obstacles. Another optional element is collecting at least five apples representing the five portions of fruit and vegetables per day. After finishing the activity, the player receives a summary of the consumed and burned calories. The success in stars is based on the divergence from a zero balance. Details for each component of the prototype are reviewed in the previous chapter 5.

6.3 evaluation

The pilot study of the *Fit Food Fun* prototype was conducted as both a pre-/post-test design comparing the changes in knowledge and motivation and a between-subject design comparing the classical teaching to our serious game solution. Each condition was conducted in one of two secondary schools in the district of Rosenheim (Bavaria, Germany) with a duration of 5 days, Monday to Friday. All participants were in the 7th, or 8th grade had volunteered for the participation and had provided written parental consent. The study has further been approved by the Ethical Committee of the School of Medicine, Technical University of Munich (number: 175/18 S), and by the Rosenheim school board (Bavaria, Germany).

6.3.1 *Study Procedure and Participants*

The study was conducted over five consecutive days, Monday to Friday. On Monday, the participants were measured (height and weight) and filled in the pre-test survey for 30 minutes. Each participant received a unique ID used for the measurements, the pre- and post-survey, and the game's login. On Tuesday to Thursday, the participants either received 15-minute lectures or played the *Fit Food Fun* game for 15 minutes. On Friday, the participants filled in the post-test survey for 30 minutes and received a small token of appreciation - a cup filled with dried fruits and an enable notepad and pen. Both the serious game and the teaching intervention focussed on six of the "10 guidelines of the German Nutrition Society" (Jungvogel et al., 2013). In the gameplay group, the participants were divided into groups of 10 people, to enable simultaneous usage of all devices (Samsung Tab S2 T813; Android 7.0; Samsung, Seoul, South Korea). The intervention was overseen by two to five study assistants to provide quick support in case of technical issues. There were no teachers present during the intervention. The teaching group was conducted by the same single study assistant to ensure similar conditions. The participants in the teaching condition were not divided. Instead, the 15-minute session was conducted within the current classroom with the current teacher present. On each of the three days, two DGE rules were written on the blackboard, discussed with the students, and reiterated in interactive quizzes.

The participants were recruited via the teachers of all 7th and 8th classes of the two study schools. The final sample was part of two 7th and one 8th grade class per school. Any student with parental consent and sufficient German skills could participate in the intervention. The initial study sample consisted of 95 students. After excluding participants due to missing data, 76 participants were eligible for the analysis of knowledge gain published in (Holzmann et al., 2019b). For the further analysis of motivational aspects in this chapter, four additional participants had to be excluded. The final sample consists of 33 participants in the game group and 39 in the teaching group. A detailed description of the study sample is published in our paper (Holzmann et al., 2019b). The sample has a slightly lower average age of 12.8 years in the teaching group than the gaming group with 13.5 years (Holzmann et al., 2019b). Further characteristics between the two samples in terms of BMI, the importance of and attention to healthy eating, and moderate physical activity, are not significantly different between the two intervention participant groups. However, there is a tendency of differences that might accumulate influence motivational aspects, such as a higher percentage of overweight, obesity, and low physical activity scores within the gameplay study sample. The actual eating behavior across both groups was measured with a food-frequency questionnaire and showed acceptable ranges for most participants.

Table 8: Overview of variables assessed and questionnaires used in this study.

Scale and Reference	Values	Timing
Demographics	Age, Grade, Gender	Pre
My BMI 4 Kids (Arbeitsgemeinschaft Adipositas im Kindes- und Jugendalter, 2011)	Weight, Height, BMI	Pre
10-item Big Five Inventory (BFI10) (Rammstedt et al., 2013)	Neuroticism, Openness, Diligence, Extraversion, Compatibility	Pre
Susceptibility to Persuasion Scale (STPS) (Kaptein et al., 2009)	Reciprocation, Scarcity, Authority, Commitment, Consensus, Liking	Pre
Brainhex (Nacke et al., 2014)	Seeker, Survivor, Daredevil, Mastermind, Conqueror, Socialiser, Achiever	Pre
Treatment SelfRegulation Questionnaire (TSRQ) (Levesque et al., 2006)	Autonomous, Controlled, Amotivation	Pre
Food Frequency Questionnaire (FFQ) (Beckert-Zieglschmid and Brähler, 2007)	Food, Drinks, Both	Pre
Leisure Time Physical Activity Summer and Winter (Strobl et al., 2014)	No Activity, Moderate Activity, High Activity	Pre
Perceived Importance of Healthy Eating	5 Point Likert Scale	Pre
Perceived Intention of Healthy Eating	5 Point Likert Scale	Pre
Action Logging	Country, Game, Screen, Points, Stars, DGE Rules	During
Intrinsic Motivation Inventory (IMI) (McAuley et al., 1989)	Enjoyment, Choice, Competence, Pressure	Post
System Usability Scale (SUS) (Brooke et al., 1996)	Score	Post
User Experience Questionnaire (UEQ) (Schrepp et al., 2014)	Scores	Post
Screens Liked	5 Point Likert Scale per Screen	Post
Learned from Screens	5 Point Likert Scale per Screen	Post
Perceived Usefulness (Venkatesh and Bala, 2008)	Score	Post
Knowledge (Holzmann et al., 2019b)	DGE, Food, and Activity Knowledge	Pre and Post
Motivation by Theory of Planned Behaviour (TPB) (Ajzen, 2002) and (Orji et al., 2017a)	Intention, Attitude, Self-Efficacy	Pre and Post

6.3.2 *Data Collection*

During the study, five different categories of data were collected. An overview of all questionnaires used in this study is given in table 8. First, the participants' height and weight were measured, and their basic demographics (age, grade, gender) were assessed. Second, self-reported data on the participant's eating behavior (FFQ) and personality (BFI10 (Rammstedt et al., 2013), STPS (Kaptein et al., 2009), BrainHex (Nacke et al., 2014), TSRQ (Levesque et al., 2006)) were collected within standardized questionnaires during the pre-test survey. Third, the interaction with the game and the success during the mini-games were logged by the devices. Fourth, the experience during the intervention was assessed with standardized (SUS (Brooke et al., 1996), UEQ (Schrepp et al., 2014), IMI (McAuley et al., 1989), Perceived usefulness (Venkatesh and Bala, 2008)) and self-developed (favorite screens, useful screens) questionnaires. Fifth, the knowledge of, attitude towards, efficacy to, and intention on healthy eating was measured before and after the intervention with self-developed questionnaires.

6.3.2.1 *Demographics and Anthropometry*

At the beginning of the pre-test survey, each participant was assessed by a team of two study assistants. The grade was derived from the participant schedule. The gender was assessed optically and the age verbally. Afterward, each participant's anthropometric measures were assessed without shoes or jackets but otherwise fully clothed. The weight was measured with a digital flat scale to the nearest 0.1 kg. The height was measured with a mobile stadiometer to the nearest 0.1 cm. The BMI percentiles were derived from both height and weight measures and used for calculating the weight status using "my BMI 4 Kids". The weight and height were further inserted into the participants' game profiles to personalize the energy expenditure during physical activities.

6.3.2.2 *Personality and Behavior*

The personality type was assessed with four different standardized questionnaires. The Big-Five-Inventory-10 (BFI-10) (Rammstedt et al., 2013) was used to get a general impression on the participants' personality. The questionnaire uses ten questions to derive insight into the five personality factors extraversion, neuroticism, openness, diligence, and compatibility. We wanted to assess this personality since studies show relations between personality types and health behavior (Roberts et al., 2007). The STPS, on the other hand, focusses on how the behavior of each participant can be influenced externally. The questions for STPS were taken from Kaptein et al. (Kaptein et al., 2009) and test the concepts reciprocation, scarcity, authority, commitment, consensus, and liking. The BrainHex questionnaire (Nacke et al., 2014) instead focusses on personality traits relevant to gaming behavior and experience by classifying the participants into one of the seven gamer types: achiever, conqueror, daredevil, mastermind, seeker, socializer, and survivor. While each person is interested in multiple gaming strategies, the prominent gamer type provides insights into which types of games are most interesting to the user. The fourth questionnaire is the treatment self-regulation questionnaire (Levesque et al., 2006), which derives which motivational regulators - autonomy, control, or amotivation - influence the participant's health behavior. Williams et al. (Williams et al., 2004) show that autonomously motivated participants have higher success in changing health behavior. The dietary behavior was assessed with a food frequency questionnaire using 45 items (Beckert-Zieglschmid and Brähler, 2007). The intake was split into eight food and five beverage groups. The intake in each group was separately categorized to be adverse (1), acceptable (2), or optimal (3) by our nutrition experts. The overall behavior score was calculated as an average of these 13 group categorizations. The leisure-time physical activity was separately measured for summertime and wintertime activities on a scale, according to Strobl et al. (Strobl et al., 2014). The resulting values were categorized into overall scores of no activity, moderate activity, and high activity using (Strobl et al., 2014). Finally, two single choice questions assessed the perceived overall importance of healthy eating and the perceived overall healthy eating intention.

6.3.2.3 *Interaction during Intervention*

During the serious game intervention, each interaction with the game is logged. This logging tracks the current user, the current time, the context (country, game, screen), and the action executed within the game. The logging includes essential parameters of the current context, such as the number of points and stars received for the success screen, or the DGE rule displayed on the loading screen, or the food items and nutrient categories for mini-game 1 and 2 or the activity type, time, and calories packed for mini-game 3. In the teaching intervention, no measures were taken during the sessions.

6.3.2.4 *Perception of Intervention*

The perception of the interventions is measured for both intervention types using the Intrinsic Motivation Inventory (IMI) (McAuley et al., 1989). With these scales, we extract the enjoyment, competence, choice, and pressure that the participants felt during either the gameplay or the teaching. In addition to the general perception of both interventions, we evaluate the opinion on the *Fit Food Fun* game in more detail. We survey the usability of the game with a System Usability Scale (SUS) (Brooke et al., 1996) and the user experience with the User Experience Questionnaire (UEQ) by Schrepp et al. (Schrepp et al., 2014). Finally, we ask the participants for each element of the game how much they liked it overall and how much they considered it useful regarding learning.

6.3.2.5 *Effects of Intervention*

Several additional questionnaires were asked before and after the intervention in both groups to measure the intervention's effects. The primary outcome of nutrition knowledge was measured on two scales. The first scale assesses the explicit knowledge of the six DGE rules by filling four blanks in each rule. Each blank counts as one knowledge point leading to 24 reachable points. The second scale assesses general nutritional knowledge by asking about energy, macronutrients, fruits and vegetables, sugar and salt, water, and beverages, and two questions on physical activity. A full-text description of the survey questions is available in (Holzmann et al., 2019b). Each question allows the participant to score one point towards a total of 13 points. Together, both scales could add up to 37 knowledge points. A detailed evaluation of the knowledge effects has been published in (Holzmann et al., 2019b). This chapter instead focuses on motivational factors within the study. To measure the motivation towards healthy nutrition before and after the intervention, three questionnaires built on the theory of planned behavior (Ajzen et al., 1991) were used to extract intention, attitude, and perceived behavioral control of the participants. The three questionnaires had been developed according to (Ajzen, 2002) by Orji et al. in their evaluation of a different game for healthy nutrition (Orji et al., 2017a).

6.3.3 *Results*

This chapter focusses on the factors influencing the different measurements. As Baranowski says, these types of mediators have to be researched in more depths (Baranowski et al., 2019a). Further, Horne states that the theory of planned behavior (Ajzen et al., 1991) is essential to be integrated into healthcare for behavior change (Horne et al., 2017). While FFF's primary goal was to increase knowledge, it was anticipated that gaining this knowledge might also influence the attitude, efficacy, intention, and finally, the behavior. The behavior was not measured post-intervention since any update in the FFQ after only three days was not to be expected. The following sections explore the interdependencies of personality, initial behavior, intention, attitude and efficacy, the intervention, and its perception and the outcome measures.

6.3.3.1 *Effects between Pre- and Post-test*

Four concepts were measured both before and after the intervention: The knowledge of the participants, their attitude towards healthy eating, their self-efficacy to eat healthily, and their intention to eat healthily. As discussed in detail in our paper (Holzmann et al., 2019b), the knowledge increased in both the game group and the teaching group. The general knowledge gain was not significantly different between the two groups, but the knowledge gain concerning the rules of the DGE was higher in the teaching group (Holzmann et al., 2019b). All effects are listed in table 9.

Table 9: N = number; p = p-value; Difference is given by the proportion of achieved points relative to the maximum of achievable points. The category "overall knowledge" is the combination of the total "rules" knowledge and the total "miscellaneous" knowledge. The table has been adapted from (Holzmann et al., 2019b).

Knowledge	Gameplay Group (GG)				Teaching Group (TG)				Difference
Category	N	Pre	Post	p	N	Pre	Post	p	p
DGE Rules knowledge	25	0.25	0.33	0.02	40	0.24	0.39	<0.0001	0.02
Misc. Nutrition and Physical Activity Knowledge	35	0.43	0.57	<0.0001	40	0.39	0.56	<0.0001	0.3
Overall knowledge	24	0.31	0.42	0.001	40	0.29	0.45	<0.0001	0.01

In contrast to the clear effect on knowledge, the attitude (p-value=0.71, mean(x)=5.04, mean(y)=4.98), efficacy (p-value=0.32, mean(x)=5.35, mean(y)=5.56), and intention (p-value=0.1 mean(x)=5.11, mean(y)=4.69) have no clear effect between pre- and post-measures. For attitude and intention, the mean value is even lower after the intervention. These mixed results can be explained by counteracting results in both groups. While the mean of intention has lowered in the teaching group (p-value=0.29, mean(x)=5.11, mean(y)=4.73), it has increased in the gaming group (p-value=0.20, mean(x)=4.66, mean(y)=5.12). Similarly, the mean attitude has decreased in the teaching group (p-value=0.35, mean(x)=5.23, mea(y)=5.03) and increased in the gaming group (p-value=0.62, mean(x)=4.79, mean(y)=4.91). For efficacy, both groups have slightly elevated their means. While the game group (p-value=0.25, mean(x)=5.08, mean(y)=5.44) shows a higher increase, the teaching group already start with a higher prior level (p-value=0.77, mean(x)=5.57, mean(y)=5.65). This bias in prior values is shown in figure 23 for intention, figure 24 for attitude, and figure 25 for efficacy. The figures show the differences in the pre- and post-measure for each group. Additionally, they differentiate between gender to show how different groups of participants react to the same intervention. In the case of intention (figure 23), the teaching group

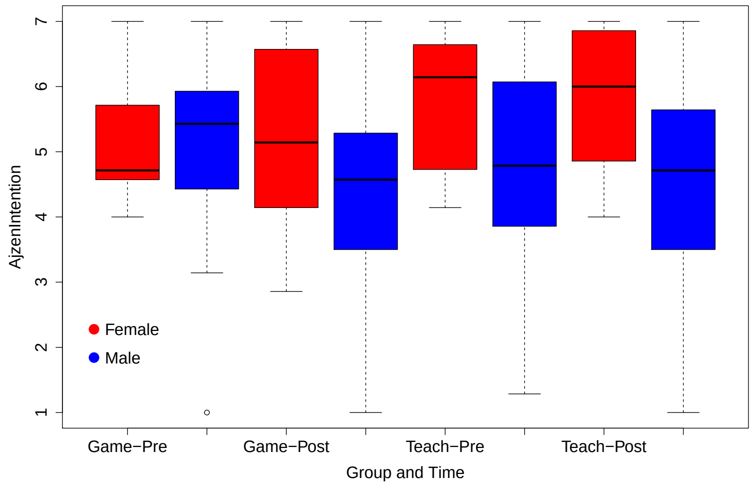


Figure 23: Intention of participants split by group, time, and gender.

has a very low variation between pre- and post-measure, but the female participants start on a much higher level than their male classmates. In the gaming group on the other side, the male/female gap is not as high, but the female participants increase their intention, while their male classmates reduce it. In the case of attitude (figure 24), the male participants stay the same between pre- and post-measure. Also, the female participants have low variation. Only a slight increase in the gaming group and a slight decrease in the teaching group are visible. Finally, the efficacy (figure 25) increases for males in the gaming group and females in the teaching group. Still, it stays stable for females in the gaming group and males in the teaching group.

6.3.3.2 *Model Selection*

After seeing changes in the motivational effects (attitude, efficacy, intention) between the previously discussed four conditions (game, teaching, female, male), we start to analyze the complete interdependencies of all mediating variables in our study. We chose Bayesian Belief Networks (BBN) (Pearl, 1985) due to their applicability to low

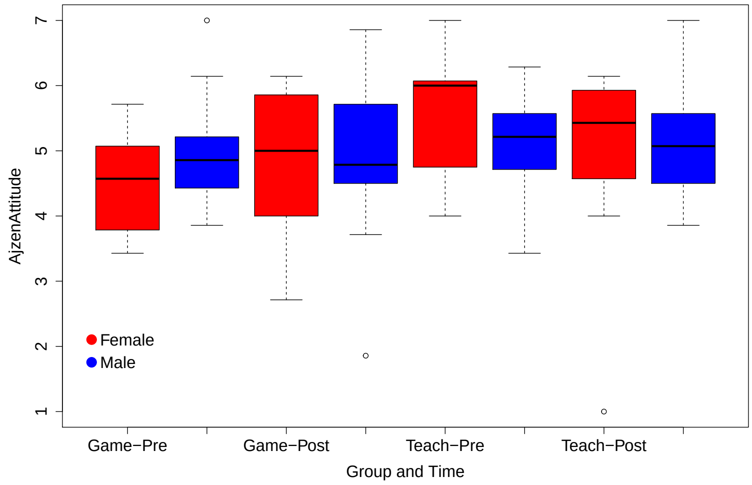


Figure 24: Attitude of participants split by group, time, and gender.

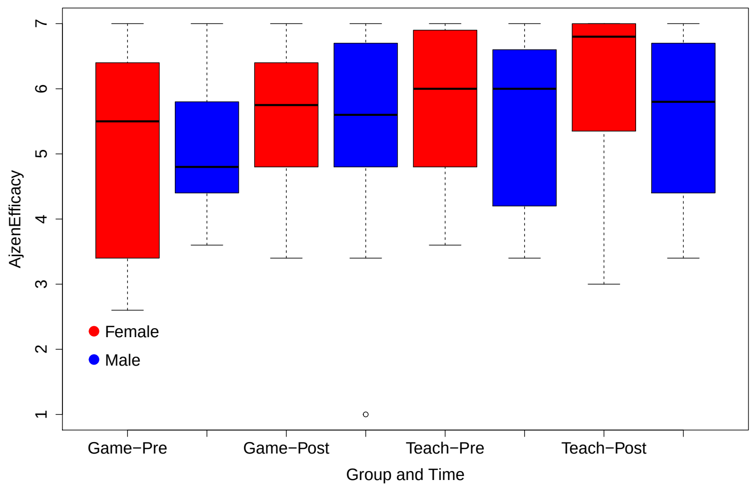


Figure 25: Efficacy of participants split by group, time, and gender.

sample sizes. We checked for normality (see figure 26) and collinearity (see figure 27). The distributions (figure 26) of the post-test measurements for attitude, efficacy, and intention are shifted towards higher values compared to the pre-test measurements. While this reduces the apparent normality, it also shows a slight effect on these motivational variables due to the intervention. Also, the pre-test efficacy and BMI measurements show noisy distributions of data. The collinearity analysis further confirms that the data is noisy due to the low sample size (figure 27). Further, the interdependency of each variable on many other variables could explain the lack of clear one-on-one correlations in figure 27, as discussed in Simpson's paradox (Wagner, 1982). Overall it seems possible to apply BBN, but the results should be interpreted with care due to the low sample size and high noise.

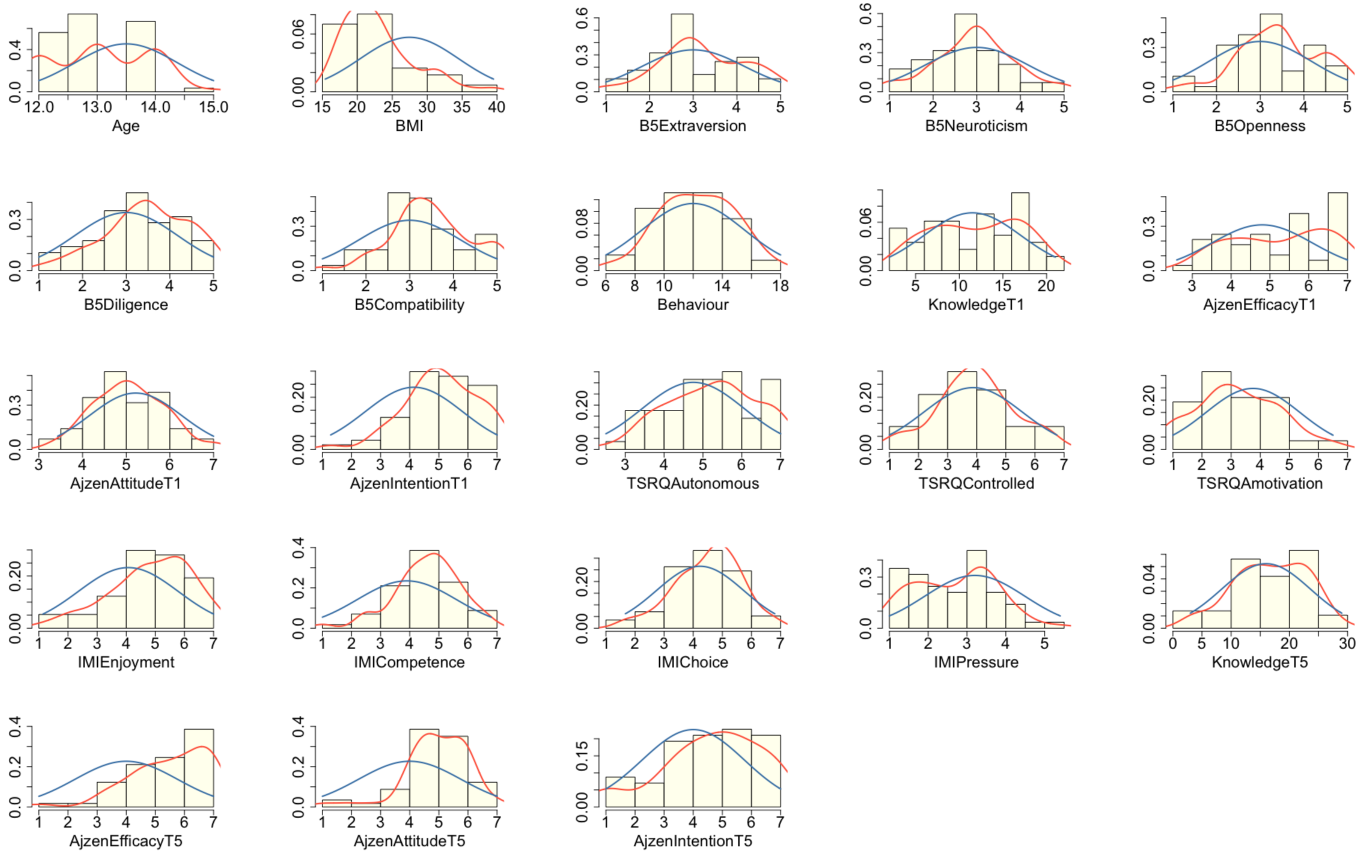


Figure 26: This collection of histograms shows the normality check of variables measured in the *Fit Food Fun* pilot study. Many variables show a skewed distribution. T1 indicates measurements before the study and T5 measurements after the study. B5 is short for the Big Five personality types.

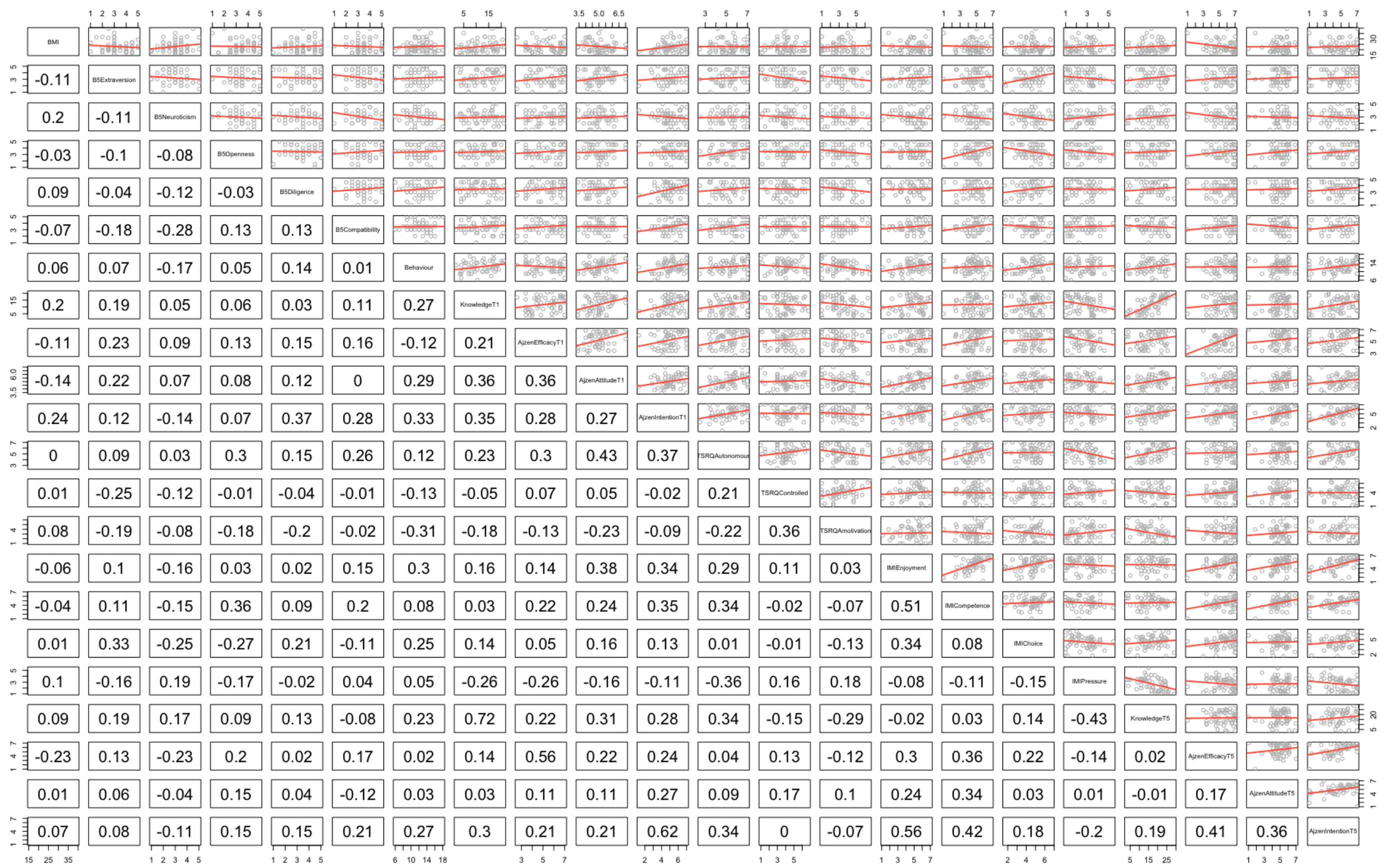


Figure 27: This scatterplot matrix shows the colinearity check of variables measured in the *Fit Food Fun* pilot study. Many variable correlations show noise. T1 indicates measurements before the study and T5 measurements after the study. B5 is short for the Big Five personality types.

After determining the preconditions, we built our BBN with two different basic structure learning algorithms that try to solve the complex optimization problem of selecting the appropriate edges between the given nodes(Scutari, 2009). As a score-based algorithm we used the Hill Climbing (HC) algorithm (Russell Stuart and Norvig, 2009). Score-based approaches assign a quality score to the network and then conduct a heuristic search in the space of possible networks. The Hill Climbing (HC) algorithm we selected is a greedy version of such a heuristic search, which is often used for score-based structural learning. As a constraint-based structure learning algorithm, we used the Interleaved Incremental Association Learning Algorithm (Inter.IAMB) (Yaramakala and Margaritis, 2005). Constraint-based algorithms analyzed the probabilities in the underlying data to build the structure in three steps. First, the undirected edges are selected based on a restricted search over each node's Markov blanket. Second, the direction of node triplets that form a v-structure is determined. Third, all missing edges are directed without allowing any cycles.

In our study, the Hill Climbing (HC) algorithm finds a multitude of connections that should be further filtered by limiting the search space. The Inter.IAMB algorithm, on the other hand, finds only a very low number of connections in our dataset, which might be caused by the issues in normality and collinearity discussed before. Both results further suffer from inverted connections, such as the post-test efficacy having a directed edge to the pre-test efficacy. To limit the network to reasonable connections, we built a dependency order of variables for each condition (figure 28). We forbid any connection from a higher level (e.g., post-test) to a lower level (e.g., basic demographics) as a blacklist in the learning process. The only difference between the overall model and the teaching model is the group (blue) variable. On the other hand, the gaming data has additional variables (yellow) concerning the game interaction and perception. Finally, the backward connection from intention to either attitude or efficacy was added to the blacklist in line with (Madden et al., 1992).

Once the blacklist was added, we can compare the quality parameters of these networks by calculating the Akaike information criterion (AIC), Bayesian information criterion (BIC), and Log-Likelihood (LogLik) scores. The BIC score was developed by Gideon Schwarz (Schwarz et al., 1978) as a criterion to select between different models. Generally, lower BIC values are preferred. The BIC score is similar to the AIC score (Akaike, 1974), since they are both based on the likelihood function. One main difference between the two criteria is that BIC has a stronger penalization to overfitting by adding parameters. Thus BIC would rather choose smaller models and AIC rather larger models. A comparison of these model quality metrics between Inter.IAMB, and different variants of the HC model is given in 10. In the software used for this evaluation, the AIC and BIC scores are rescaled by -2. Thus, higher values in measured scores indicate better models. Due to the dataset's limited size, these scores are calculated on the same dataset used to learn the structure. While this may lead to overfitting, it can still gain insights into differences between the model's variants. The reason for providing different HC models is to improve the reliability of its greedy search results. We do this by applying bootstrapping to the model and then selecting a strength threshold to build the average network structure. Bootstrapping was first introduced by Friedman, Goldszmidt, and Wyner (Friedman et al., 1999) to quantify confidence in network estimates. In our network's bootstrap algorithm (Imoto et al., 2002), the

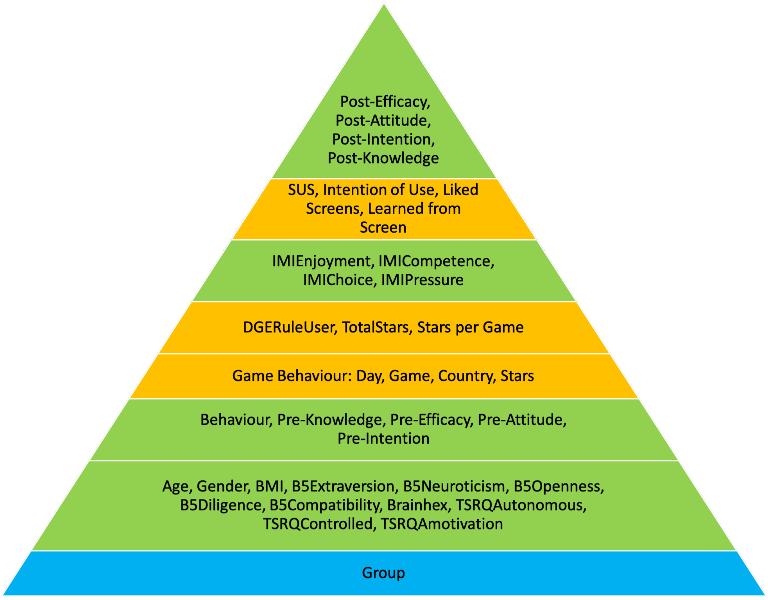


Figure 28: This pyramid shows the hierarchy of variable dependencies in the *Fit Food Fun* pilot study. The dependency hierarchy is used to derive a blacklist of connection in the belief network. For example, the post-measurements on top of the pyramid cannot influence any variables below. The yellow color indicates variables that are only available in the gaming group. The blue color indicates that the group variable is only available in the joint dataset.

probability edges and their direction is calculated as a value of strength. We can then build a network that only includes edges above a certain threshold, which further leads to acyclic networks, except if both directions have the same strength. The distribution of strength values for each of our datasets is shown in figure 29. It also highlights the different threshold tested in our model selection process. The default threshold suggested by the algorithm is 0.5. Between the different HC models, the quality metrics indicate that models with a higher threshold, tested at 0.65, perform worse, and models with lower threshold perform better on all three datasets and metrics. However, if the threshold is set too low, the network will start to become cyclic. These cycles happen at 0.33 for the teaching dataset, at 0.45 for the overall dataset, and already at 0.51 for the gaming dataset. Since the teaching and overall dataset improvements for lower thresholds were only slight, we chose the threshold of 0.51 as the lowest common threshold for all three networks as the final models. In comparison to the three HC models, the Inter.IAMB model performs similar to the highest threshold, fitting the stricter selection of edges in constraint-based structure learning. Unfortunately, the Inter.IAMB model did not work on the gaming dataset at all. The reason might be additional gaming variables, which lead to a higher imbalance between the number of features and the number of samples.

The final network with strength encoded as the thickness of edges is shown in figure 30 for the overall dataset, in figure 31 for the game subset, and in figure 32 the teaching subset. Due to a slight imbalance in the number of included participants (N=57), the overall model is more similar to the teaching model (N=33) than the game model (N=24). The overall model further has a number of connections that

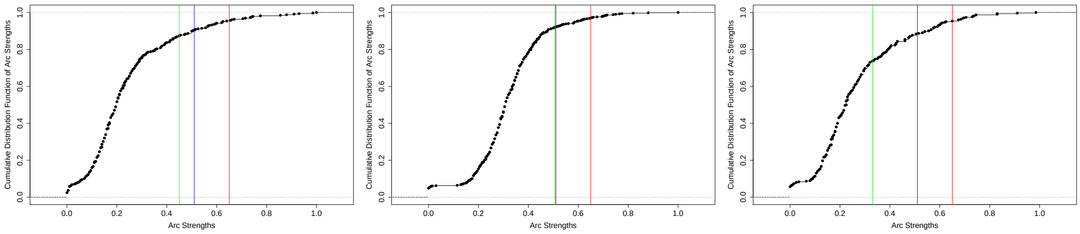


Figure 29: Arc-strength distribution plot for the full dataset (left), game dataset (middle), and teaching dataset (right). The green line shows the lowest threshold possible for this dataset without errors. The blue line shows the lowest common threshold of 0.51, and the red line shows a higher threshold that is compared at 0.65.

Table 10: Comparison of model quality between Inter.IAMB, and the three different strength thresholds of the Hill Climbing (HC) model.

	Overall Inter.IAMB	**Overall Min 45**	**Overall 65**	**Overall 51**
AIC	-2456	-2393	-2437	-2406
BIC	-2527	-2500	-2512	-2500
LogLik	-2386	-2288	-2364	-2314
	Teaching Inter.IAMB	**Teaching Min 33**	**Teaching 65**	**Teaching 51**
AIC	-1388	-1332	-1384	-1343
BIC	-1436	-1468	-1437	-1417
LogLik	-1324	-1151	-1314	-1245
	Game Inter.IAMB	**Game Min 51**	**Game 65**	**Game 51**
AIC	-Inf	-1454	-1492	-1454
BIC	-Inf	-1517	-1540	-1517
LogLik	-Inf	-1347	-1410	-1347

don't appear in either subset but become relevant when using the full dataset, such as the influence of the groups on age, which also influences the participants' initial knowledge.

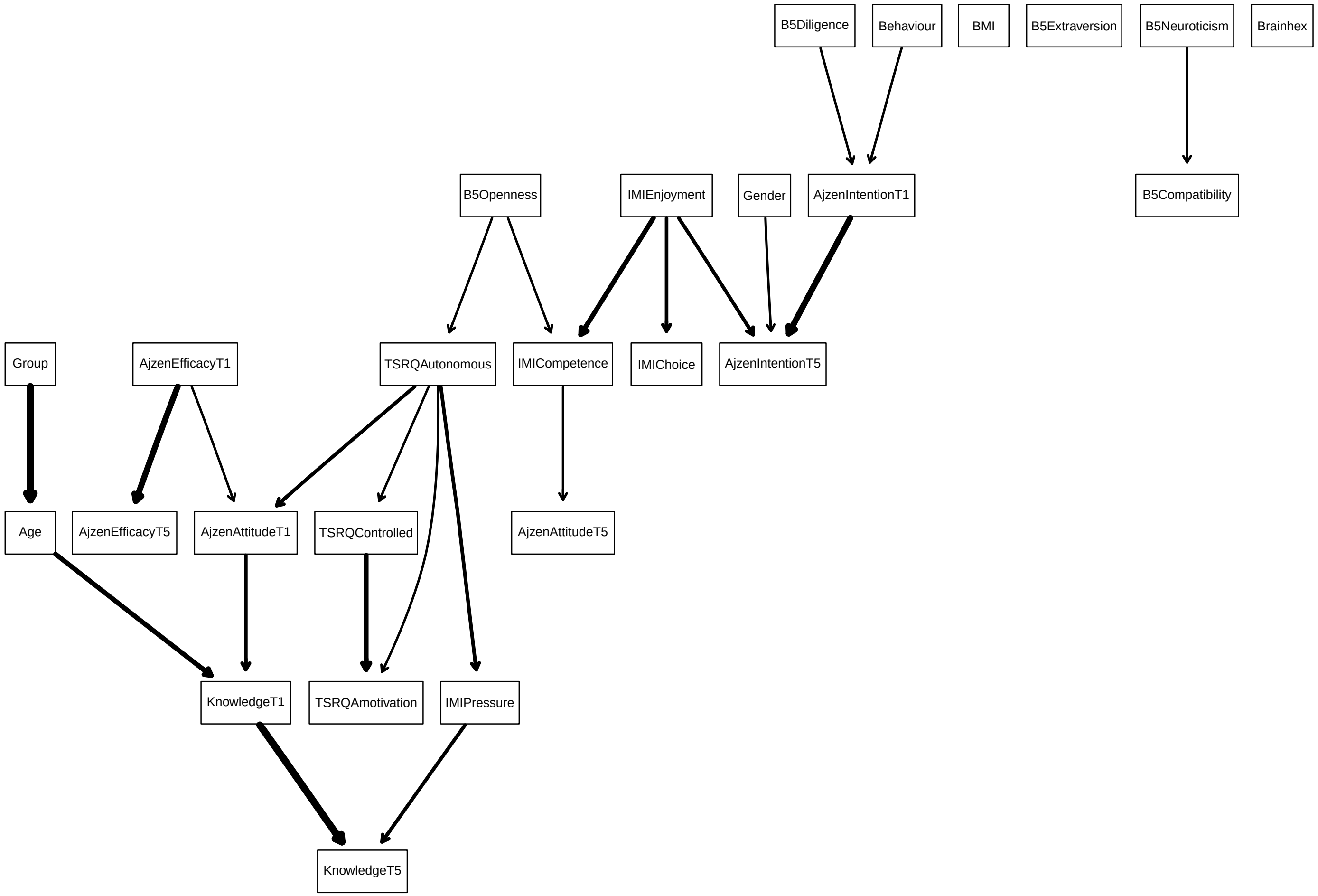


Figure 30: Final average strength graph of the Hill Climbing (HC) for the overall dataset with an arc-strength threshold of 0.51.

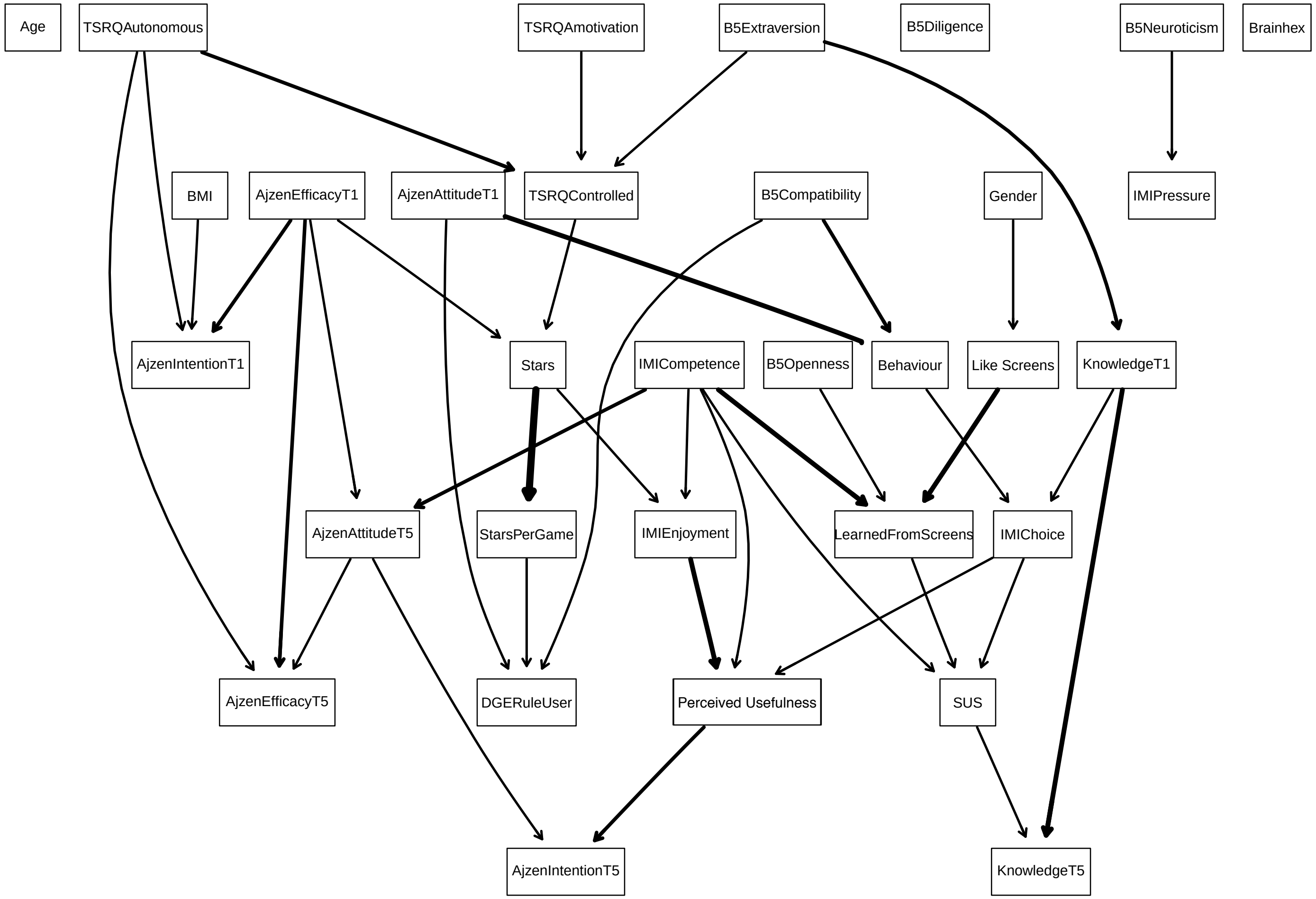


Figure 31: Final average strength graph of the Hill Climbing (HC) for the game dataset with an arc-strength threshold of 0.51.

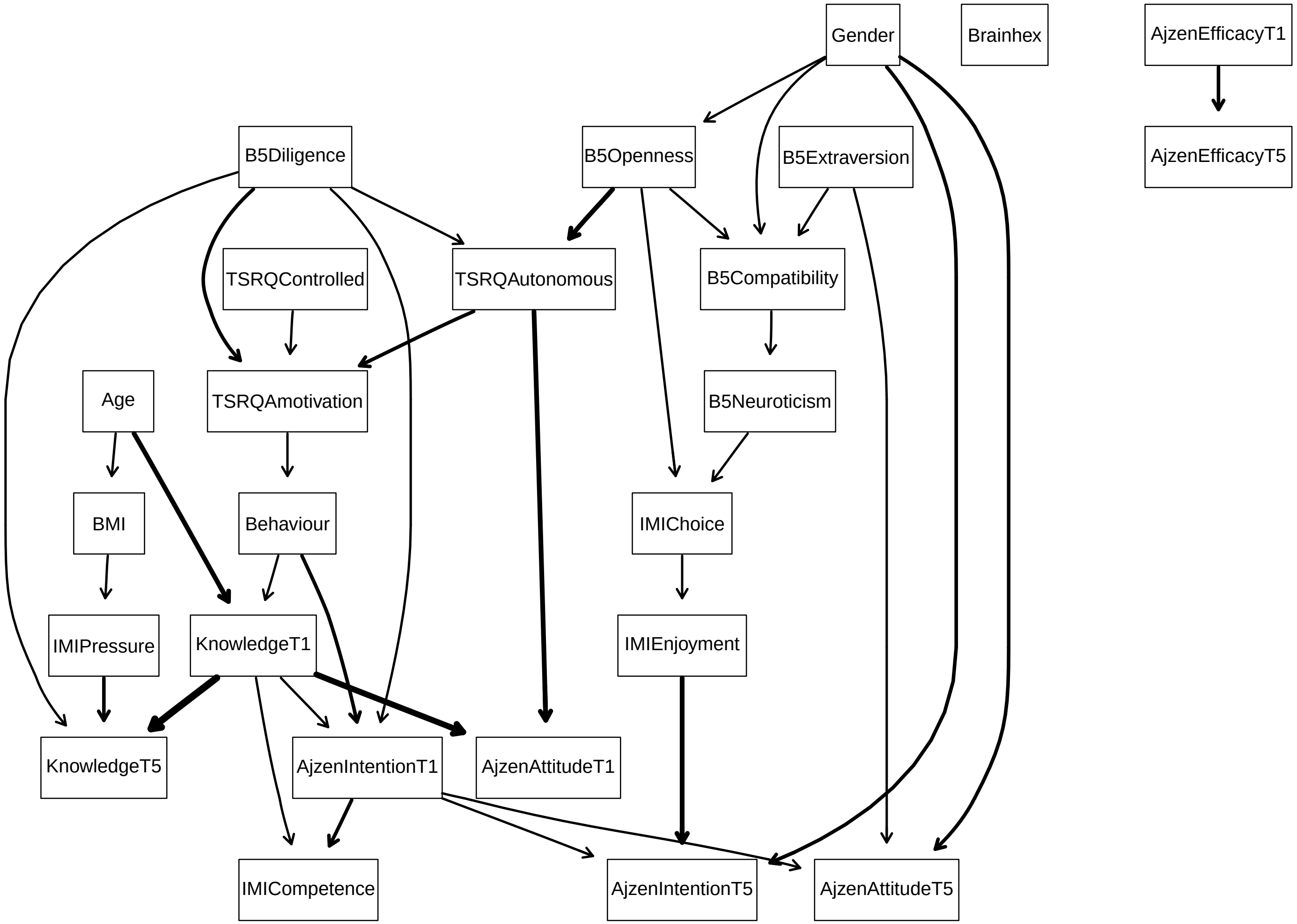


Figure 32: Final average strength graph of the Hill Climbing (HC) for the teaching dataset with an arc-strength threshold of 0.51.

6.3.3.3 *Mediators between Intervention effects*

To investigate the indicated pathways, we use linear models for each of the individual nodes and extract the parameters of its incoming edges. For example, if we want to evaluate the mediating parameters of the post-study knowledge in the teaching condition. After retrieving all relevant incoming edges to this node in our network, we build a linear model with the target variable depending on these edges' nodes. The edge retrieval already provides estimates for each incoming node's coefficients, which are identical to the coefficients delivered by the linear model applied to these variables. Additionally, the linear model provides us with information on the Standard Error (s.e.), and p-values of the incoming edges analyzed independently from other network connections. An overview of the resulting estimates is given in table 11.

The final knowledge of the participants depends on prior knowledge (est=0.78, s.e.=0.11, p=2.3e-09***) and negatively on perceived pressure (est=-1.58, s.e.=0.54, p=4.6e-03**) in the overall dataset. In the teaching subset, knowledge (est=0.77, s.e.=0.12, p=6.1e-07***) and pressure (est=-1.71, s.e.=0.66, p=0.01*) are important as well, and diligence (est=1.36, s.e.=0.63, p=0.04*) is an additional influencing factor. In contrast, the SUS (est=0.10, s.e.=0.07, p=0.16) is the only additional influence on knowledge (est=0.69, s.e.=0.20, p=2.5e-03**) in the game model. However, the SUS on its own is not a significant influence variable, and its effect in the network might be related to its incoming paths. In the model with a higher threshold, this connection vanishes. The main positive factor of previous knowledge on the posterior knowledge in both conditions is expected and indicates a reasonable assessment of knowledge. The impact of pressure in the learning condition might be related to the pressure students are used to feel in lecture-like situations where their performance is evaluated. In a gaming context, on the other hand, no performance pressure is associated with the experience. This preconditioning of the lecture context is further in line with diligent people thriving more since their personality might favor the lecture and performance context.

The final intention of the participants depends on the gender (est=0.82, s.e.=0.35, p=0.02*), pre-test intention (est=0.59, s.e.=0.13, p=4.7e-05***), and enjoyment of the intervention (est=0.47, s.e.=0.12, p=1.7e-04***) in the overall dataset. In the teaching subset gender (est=0.71, s.e.=0.43, p=0.12), pre-test intention (est=0.43, s.e.=0.16, p=0.01*) and enjoyment (est=0.83, s.e.=0.16, p=2.2e-05***) are important as well. Gender is not significant in the teaching context, which could be due to the smaller sample size. In contrast, the post-test attitude (est=0.57, s.e.=0.20, p=0.01**), and the perceived usefulness (est=1.07, s.e.=0.30, p=1.8e-03**) are the only influence in the game model. Surprisingly, in the game context, the post-test intention is not directly dependent on the pre-test intention. The influence of gender on intention, efficacy, and attitude was already visible at the beginning of this chapter. However, since it is not significant in either condition and only in the joint dataset, this effect might be due to the sample variance instead of an actual effect. Since the attitude is one input to behavioral intention, according to Ajzen et al. (Ajzen et al., 1991), this correlation in the gaming condition might indicate that the attitude has changed, which in turn influenced the intention. This impact is not visible in the teaching condition, where only the prior intention is of influence. It is further a relevant insight, that enjoyment is the primary impact on post-intention in both conditions, with perceived usefulness being highly correlated to the enjoyment and thus interchangeably used in the model.

The final efficacy of the participants depends positively on the pre-test efficacy (est=0.69, s.e.=0.12, p=6.6e-06***) in the overall dataset and in the teaching (est=0.56, s.e.=0.15, p=9.2e-04***). The game model also includes the pre-test efficacy (est=0.49, s.e.=0.21, p=0.03*) and it is additionally positively dependent on the post-test attitude (est=0.53, s.e.=0.22, p=0.02*), and negatively on the autonomous motivation (est=-0.40, s.e.=0.19, p=0.05*). Just as in the context of behavioral intention, the post-attitude is relevant for the post-efficacy. Since attitude can influence efficacy, according to Ajzen et al. (Ajzen et al., 1991), this correlation in the gaming condition is another indication of a change in attitude. This impact is again not visible in the teaching condition. The negative impact of autonomous motivation on efficacy in the game context could be explained by negative feedback or loosing in a context where autonomously motivated participants might have expected to succeed with ease.

The final attitude of the participants is only influenced significantly by the perceived competence in both the overall dataset (est=0.3257, s.e.=0.1223, p=0.0101*) and the gaming dataset (est=0.52, s.e.=0.13, p=0.01*). Since there is no indication of any significant impact within the teaching condition, the overall dataset's effect might represent the gaming condition's effect. Having a positive effect by perceived competence in the gaming context is in line with the negative effect of perceived pressure in the teaching context. Seemingly, the game provided either easier tasks or conveyed a feeling of a safe learning environment. In line with the perceived competence is the pre-efficacy of participants (est=0.42, s.e.=0.15, p=0.01*), which might naturally lead to more perceived competence and thus to a similar effect on attitude. Overall, these effects confirm the indication that the gaming context positively influenced participants' attitudes, which the teaching context did not. This change in attitude was previously shown visually, but could not be captured statistically due to the low sample size. However, different mediators' effects provide a structured derivation of why such an effect is probably a systematic result of conditions instead of a random effect due to noise.

Many connections in the graph are weaker links or not significant when checking the linear model. This lack of consistency could be due to high noises in the small sample and contradicting pathways caused by the two interventions. It could also be that the prior paths which are not represented in the linear model create an indirect impact on the targeted outcome variable.

Table 11: Results of linear models applied to different nodes in the graph and their dependency on incoming edges.

			Overall				Teaching				Game	
Evaluated Node	Incoming Edge	Estimate	Standard Error	P-Value	Incoming Edge	Estimate	Standard Error	P-Value	Incoming Edge	Estimate	Standard Error	P-Value
PostKnowledge	PreKnowledge	0.78	0.11	2.3e-09***	PreKnowledge	0.77	0.12	6.1e-07***	PreKnowledge	0.69	0.20	2.5e-03**
	IMIPressure	-1.58	0.54	4.6e-03**	IMIPressure	-1.71	0.66	0.01*				
					B5Diligence	1.36	0.63	0.04*	SUS	0.10	0.07	0.16
PostIntention	Gender	0.82	0.35	0.02*	Gender	0.71	0.43	0.12				
	PreIntention	0.59	0.13	4.7e-05***	PreIntention	0.43	0.16	0.01*	PostAttitude	0.57	0.20	0.01**
	IMIEnjoyment	0.47	0.12	1.7e-04***	IMIEnjoyment	0.83	0.16	2.2e-05***	Perceived Usefulness	1.07	0.30	1.8e-03**
PostEfficacy	PreEfficacy	0.5895	0.1183	6.57e-06***	PreEfficacy	0.56	0.15	9.2e-04***	PreEfficacy	0.49	0.21	0.03*
									PostAttitude	0.53	0.22	0.02*
									TRSQAutonomous	-0.40	0.19	0.05*
PostAttitude	IMICompetence	0.3257	0.1223	0.0101*					IMICompetence	0.52	0.13	6.3e-04***
					PreIntention	0.19	0.15	0.22	PreEfficacy	0.42	0.15	0.01*
					B5Extraversion	0.16	0.21	0.46				
					Gender	-0.44	0.45	0.33				

Table 12: Results of linear models applied to different nodes in the graph showing their dependency on incoming edges in each of the datasets.

			Teaching				Game	
Evaluated Node	Incoming Edge	Estimate	Standard Error	P-Value	Incoming Edge	Estimate	Standard Error	P-Value
IMIEnjoyment	IMIChoice	0.35	0.17	0.052.	IMICompetence	0.68	0.17	6.8e-04***
					Stars	-0.05	0.02	0.00**
IMICompetence	PreKnowledge	-0.06	0.03	0.03*				
	PreIntention	0.48	0.11	1.5e-04***				
IMIChoice	B5Neuroticism	-0.59	0.22	0.01*	FoodBehavior	0.18	0.08	0.04*
	B5openness	-0.53	0.20	0.01*	PreKnowledge	0.09	0.04	0.03*
IMIPressure	BMI	0.05	0.04	0.22	B5Neuroticism	0.51	0.19	0.01*

6.3.3.4 *Perception: Enjoyment, Choice, Competence, Pressure*

As seen in the analysis of influence factors on the main effect variables, the intervention's perception plays an important role with the enjoyment impacting intention changes, the pressure impacting knowledge gain, and the competence impacting attitude. We thus elaborate on how these variables are interdependent in both conditions. An overview of the resulting estimates is given in table 12. For example, the enjoyment depends marginally significantly on the perceived choice (est=0.35, s.e.=0.17, p=0.052.) in the teaching group. In the gaming group, on the other hand, it depends positively on the perceived competence (est=0.68, s.e.=0.17, p=6.8e-04***) and negatively on the total of stars (est=-0.05, s.e.=0.02, p=0.00**) achieved in the gameplay. The negative correlation with stars could indicate that the game was too easy for most participants. However, when comparing to the previous results on the main outcomes, we see an interplay of competence, enjoyment, attitude, and finally, intention, for the gaming context. This interdependency indicates both that the game only shows the impact on participants satisfied with the game and that the game impacts these motivational aspects in contrast to the teaching condition. Perceived competence, on the other hand, is independent in the game case but based negatively on pre-test knowledge (est=-0.06, s.e.=0.03, p=0.03*) and positively on pre-test intention (est=0.48, s.e.=0.11, p=1.5e-04***) in the teaching case. However, since the competence has no impact on any outcome variables in the teaching context, these dependencies on previous intention and knowledge are less relevant. The perceived choice which influences enjoyment in the teaching case, is negatively dependent on the participant's neuroticism (est=-0.59, s.e.=0.22, p=0.01*) and openness (est=-0.53, s.e.=0.20, p=0.01*). This correlation indicates that only certain personality types feel comfortable enough in the teaching context to perceive it as voluntary. This aspect is in line with diligent personality types gaining more knowledge from in the teaching context. In the gaming context, on the other hand, the perceived choice is positively influenced by prior eating behavior (est=0.18, s.e.=0.08, p=0.04*) and pre-test knowledge (est=0.09, s.e.=0.04, p=0.03*). This correlation is in line with a positive prior relation to nutrition, leading to voluntary engagement with the topic and vice versa. Finally, the perceived pressure is slightly connected to the BMI (est=0.05, s.e.=0.04, p=0.22) in the teaching case, and positively connected to neuroticism (est=0.51, s.e.=0.19, p=0.01*) in the gaming case. This correlation might indicate that neurotic participants find it hard to succeed as expected within the game, which contrasts the previous observation of the game being too easy. This contrast might indicate another issue of personalization, where the game's difficulty level should be adapted to the user's personality and ability.

6.3.3.5 *Game internals*

In figure 31, we see that success negatively influences enjoyment and thus perceived usefulness and intention to healthy eating in the post-condition. Therefore, we investigate how the game's success (stars) in each mini-game depends on gamer personality and how much on the game's internal context. We analyze each success event in the gaming logs. In total, 1089 records by 24 users were available for this analysis. We used a multilevel regression model with the user as a random intercept and one in-

Table 13: Multilevel regression with one random intercept for users. For the model, the coefficient factor in the linear model, the Standard Error (s.e.), the z-value (coefficient divided by s.e.), and the p-value are given.

	Estimate	Std. Error	df	t-value	Pr(>{}|t|)	
(Intercept)	2.721e+00	7.300e-01	1.642e+01	3.727	0.00176	**
DGERuleUser	1.730e-03	1.064e-03	1.873e+01	1.627	0.12048	
Day	1.512e-01	5.113e-02	4.265e+02	2.957	0.00328	**
GameGame2Scene	-2.895e-01	6.887e-02	1.060e+03	-4.203	2.85e-05	***
GameGame3Scene	-2.065e-01	6.773e-02	1.059e+03	-3.049	0.00235	**
CountryDenmark	2.511e-01	9.344e-02	5.906e+02	2.687	0.00741	**
CountryNorway	1.315e-01	1.085e-01	5.024e+02	1.212	0.22591	
CountrySweden	1.856e-01	1.203e-01	4.582e+02	1.542	0.12372	
CountryFinland	4.686e-02	1.337e-01	4.498e+02	0.351	0.72607	
CountryPoland	-3.462e-04	1.668e-01	4.526e+02	-0.002	0.99834	
CountryCzechia	-5.916e-02	1.815e-01	4.571e+02	-0.326	0.74465	
CountryAustria	-4.886e-02	1.893e-01	4.803e+02	-0.258	0.79646	
CountrySwiss	-1.723e-02	2.476e-01	6.926e+02	-0.070	0.94453	
CountryItaly	-2.049e-01	3.261e-01	8.128e+02	-0.629	0.52982	
CountrySpain	-6.194e-01	3.964e-01	7.551e+02	-1.563	0.11853	
PreTestKnowledge	4.208e-02	1.301e-02	1.909e+01	3.235	0.00434	**
B5Compatibility	7.141e-02	5.634e-02	1.847e+01	1.267	0.22076	
B5Extraversion	-2.241e-05	5.836e-02	1.958e+01	0.000	0.99970	
PreTestAttitude	-3.797e-02	2.685e-02	1.531e+01	-1.414	0.17740	
PreTestEfficacy	-3.483e-02	3.520e-02	1.563e+01	-0.990	0.33742	
TSRQControlled	1.522e-02	5.595e-02	1.707e+01	0.272	0.78885	
TSRQAutonomous	-8.634e-02	4.478e-02	1.576e+01	-1.928	0.07207	.
TSRQAmotivation	-5.286e-03	3.851e-02	1.579e+01	-0.137	0.89255	
IMIChoice	-5.828e-02	5.168e-02	1.609e+01	-1.128	0.27599	
IMIPressure	2.117e-02	3.784e-02	1.641e+01	0.559	0.58351	
IMICompetence	8.242e-02	4.285e-02	1.567e+01	1.923	0.07279	.
PerceivedUsefulness	-1.928e-01	2.301e-01	1.582e+01	-0.838	0.41466	
IMIEnjoyment	-4.321e-01	1.353e-01	1.591e+01	-3.193	0.00569	**
PerceivedUsefulness:IMIEnjoyment	8.645e-02	4.577e-02	1.610e+01	1.889	0.07703	.

teraction effect to model the high interdependency between enjoyment and perceived usefulness. Our model shows the success metric stars' main influence factors when including all the previously discussed prior/posterior path variables and the game internals (see table 13).

Concerning the game internals, the model shows no impact on the time users spent looking at the DGE rules, which seems reasonable since the knowledge is only required implicitly during the mini-games. Another factor is the day in the study (1-3), which indicates a slight learning effect due to more success in later days. The model further indicates a negative impact of games 2 and 3 compared to game 1, with game 2 having the worst performance. This low performance of game 2 is in line with previous usability studies (chapter 5) reporting difficulties with game 2 (sugar/fat/salt estimation game). Concerning the countries traversed in the journey through Europe, the four countries following the baseline of Germany receive better performances, which is probably due to Germany being the first and still unknown country. The following countries reach lower success rates again. Of the prior path variables, only pre-test knowledge positively influences the success metric. The perception of the game, measured by the IMI scales and the perceived usefulness, also has one influential parameter, namely perceived enjoyment. In the model, the perceived enjoyment is correlated with less success in the mini-games. Due to their high correlation, the interaction effect of perceived enjoyment and perceived usefulness was integrated as a correcting factor. The internal analysis results in three main conclusions. First, there is a learning effect over time, which results in higher in-game success. Second, success in the game depends on previous knowledge. Third, enjoyment and success are negatively related to each other. One interpretation of this negative impact is that for participants that perceived the game as easy because they were very successful, the game was not as enjoyable. On the other hand, we previously discussed the positive impact of perceived competence on enjoyment. This contradiction could indicate that the calibration of difficulty to be challenging but not too difficult is an essential design parameter for serious games.

6.4 DISCUSSION OF RESULTS

Studies suggest that serious games can improve knowledge on healthy nutrition and in a number of cases, even improve the nutritional behavior (Baranowski et al., 2019b). The *Fit Food Fun* game has been iteratively designed and reviewed, e.g., in focus groups, for being an acceptable serious nutrition game for the respective target group (14-17 years of age). Our study shows that *Fit Food Fun* can improve the nutritional knowledge of the participants. The study further indicates that the game's motivational impact is different from the teaching sessions offered to a control group.

6.4.1 *Review of Research Questions*

Our research questions for this study concerned whether the *Fit Food Fun* game improves the knowledge, attitude, efficacy, and intention concerning healthy nutrition. We further asked how different participants (e.g. BFI10, TSRQ) reacted to the game and the teaching sessions.

Concerning the knowledge, we observe that the improvement is significant and comparable between the game and teaching group, except for the explicit DGE rules, which were learned better in the teaching group. This difference in learning exact rules and knowledge is expected, as the game is more targeted to implicit knowledge and everyday knowledge application. Another important difference between the interventions is the negative impact of pressure on the posterior knowledge in the teaching condition. This combination of insights might indicate that classical teaching instills explicit knowledge in a more effective way for good students. On the other hand, games can provide a more subtle approach to impart knowledge that imposes less pressure and instead motivates the students.

This implied impact on motivation becomes more evident in the analysis of attitude, efficacy, and intention. While the direct comparison of pre- and post-survey changes was not significant, we see a visual difference between the game group, which is improving intention, efficacy, and attitude, and the teaching group, which is decreasing intention and attitude. However, the baselines were different between groups and genders, making a precise outcome evaluation difficult. To approach this differentiation between counteracting effects, we conduct an in-depth analysis of our mediators' interdependencies. We built a BBN for the overall, gaming, and teaching group to compare the different pathways towards the final knowledge and motivational states.

Our analysis concludes that in the gaming context, the perceived competence and success influence the post-intervention attitude, which, in combination with the enjoyment during the intervention, enhances behavioral intention. Such a pathway is not visible in the teaching context, where instead, behavioral intention only depends on enjoyment, which is influenced by perceived choice triggered by personality type. A provocative interpretation would be that while the change in intention depends more on the participant's personality in the teaching context, it depends more on the participant's experience in the gaming context.

Besides this main insight gained during the analysis, there are less significant pathways, that are still of interest and should be investigated in future studies. One relevant path in the overall dataset leads from the group (game/teach) to a difference in age distribution, which leads to different initial and final knowledge. This path is essential to note since it biases the results on knowledge gain. Further, gender impacts the participants' intention and attitude in the teaching sample, but not in the gaming sample. This gender factor might be another confounding parameter in the sample selection, or it might indicate an actual gender difference impact of classical teaching, as indicated by (Duckworth and Seligman, 2006). Another relevant path in the teaching condition leads from age to both BMI and prior knowledge, which connects to the final knowledge. The BMI is further mediating the perceived pressure, which has adverse effects on the post-knowledge. This impact on pressure could indicate that classical teaching is less suited for high BMI students since they perceive more pressure, which impedes knowledge gain. Beyond the discussed motivational paths, the gaming condition provides insights into the way game perceptions are interdependent. Both SUS and perceived usefulness depend on the competence and choice experienced during gameplay. While the SUS measure is additionally influenced by how much participants like screens and think they learn from screens, the perceived usefulness of the game further depends on the enjoyment perceived during gameplay. This separation is surprising since one might have expected that the usability would rather depend on the enjoyment experience and usefulness on the feature perception. While all these paths are highly dependent on the data-sample provided and the given interventions, they still give an intuition about the confounding factors for changes in intention, attitude, efficacy, and knowledge.

Finally, we investigated the game's internal success for the impact of prior user attributes, game mechanics, and overall perception. We see that the game conditions concerning rising difficulty, learning effect, and the difference in mini-games show the expected impact. We further observe that only the prior knowledge impacts the game success. Finally, we see that the game's enjoyment is negatively imposing on the success within the game. This correlation might indicate the game's difficulty not being challenging enough, which leads to only users with high challenge and lower success enjoying the game.

6.4.2 *Study Limitations*

The study setting is limited regarding the number of participants, the sampling from different environments (one game and one teaching school), and the short duration of teaching and gaming (3 days with 15 minutes). These limitations reduce the robustness of our results in different settings, even for pre-intervention measurements. Further, gender is biased towards male participants, which showed a higher interest in participating in a games study. Finally, the study sample consists of a limited cultural area in the district of Rosenheim, Germany. Despite these restrictions, we expect the results of underlying mediators to generalize to upcoming studies with similar participant samples and interventions.

6.4.3 *Implications for Future Studies*

The study reveals dependencies in the effects of both gaming and teaching interventions. Most interestingly, it indicates that the gaming intervention positively affected motivational measurements, which the teaching condition did not. However, the results show that this effect depends on the careful calibration of gaming difficulty to the user's ability. There is a negative relation between enjoyment and gaming success that impacts the change in behavioral intention. There is also a positive effect of perceived competence towards changes in attitude, which in turn impact that same behavioral intention. This contradiction implies a need for tailored gaming experiences. Previous literature already investigated the impact of player types and personality types on gaming, e.g., (Orji et al., 2017b). However, our study shows that these types of mediators should not only be included both as configurations for personalized playing but also as constructs when evaluating health game studies. Without adding and systematically analyzing the arrangement of mediating effects, this study would only have revealed that games are less suited to transfer explicit knowledge than teaching that explicit knowledge.

6.5 Conclusion and Next Steps

In this study, we observe how the *Fit Food Fun* game influences the knowledge, intention, attitude, and efficacy of its players compared to classical teaching. The final study dataset for the knowledge evaluation consisted of 72 participants. The complete dataset for the belief networks includes 24 gaming and 33 teaching users due to individual missing values. We observe that the game improves knowledge and slightly influences motivational measures. However, the effects depend on prior motivation, user profiles, and the intervention's perception. We observe that this dependency network differs between the teaching and gaming settings. In summary, we contribute a detailed insight into the relevant dependencies of improving knowledge and motivation concerning healthy nutrition. The findings of this pilot study should be confirmed with larger sample sizes.

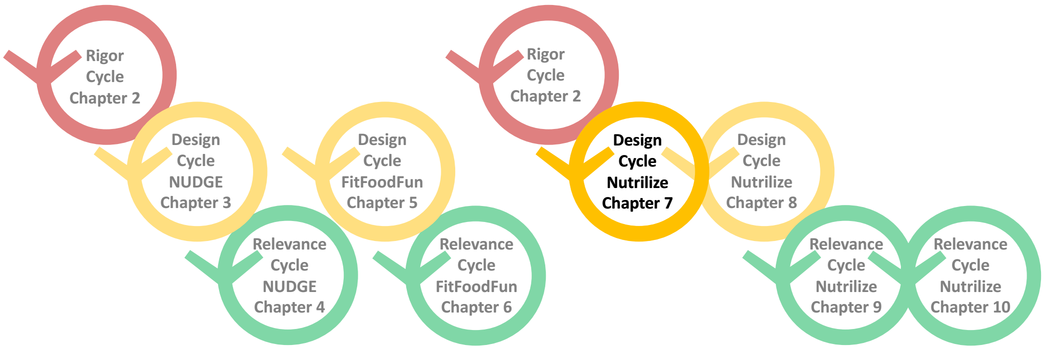
This chapter concluded the first part of this thesis focussing on socio-technical systems for healthy nutrition in children and young adults. This final relevance cycle shows the potential of such systems for knowledge communication, but also critical insights into the limitations of motivational pathways in real-life settings. We discussed in the related work section of the design chapter 5 how many previous serious games for health have succeeded in imparting knowledge in the short term. At the same time, only some lead to long-term knowledge or even behavior change. Another point extracted from the literature was a lack of knowledge of the mediating effects of serious game interventions. We investigated these mediators and their pathways towards our targeted outcome variables during our between-subject study comparing teaching and a serious game for healthy nutrition. Regarding the knowledge gain, we observe that perceived pressure was an inhibiting factor in the teaching setting, but not relevant in the gaming setting. In the same way, gender and enjoyment influenced the change in intention during the teaching setting, but not in the gaming setting, where the game's perceived usefulness played a more dominant role. For the change in attitude, perceived competence was a relevant factor for the gaming setting, but not for teaching. Finally, we note a negative effect of enjoyment on the success within the game itself. In the scope of the larger socio-technical platform *NUDGE*, we hope to steer some of these effects by combining the observed pressure-free knowledge gain with a social peer system that could utilize the effects of greater intention change in teaching-like collaborative learning situations. To address the importance of perceived competence and the contradiction between success and enjoyment, the *NUDGE* should provide tailored, and adaptive difficulty levels in the provided serious games. Additionally, similar studies with larger sample sizes or longer duration would be valuable to confirm these pathways.

Part III

CASE NUTRITION ASSISTANCE SYSTEMS FOR ADULTS

7

DESIGNING A NUTRITION ASSISTANCE SYSTEM



This chapter reviews the design process and pre-evaluations of our designed nutrition assistance system, *Nutrilize*. An early design version has been published as research in progress at the ICIS conference in 2016 (Terzimehić et al., 2016). This chapter moves beyond that design, but a few paragraphs make frequent references to this publication's content, such as our features' classification according to the persuasive system design framework (Oinas-Kukkonen and Harjumaa, 2009). This chapter opens our research on socio-technical systems for healthy nutrition in adults with a first design cycle. The design is based on a wide variety of persuasive elements observed in the literature and commercial applications reviewed during the rigor cycle (chapter 2) and additionally grounded in a review of related work on the context of personalized feedback with visualizations, recommendations, and explanations. We elaborate on each of the iterative improvements to the *Nutrilize* application. We discuss the focus of the initial design concepts on personalized nutrition via digital dietary diaries, tailored recommendations, and visual feedback. Each focus component is iteratively improved and evaluated. We further perform an initial design iteration on a social component for such a nutrition assistance system, which is not included in the subsequent second design cycle.

7.1 MOTIVATION

According to the requirements derived during the rigor cycle in chapter 2, the design of our socio-technical system supporting healthy nutrition for adults should meet the following criteria:

1. Inclusion of self-monitoring and other behavior change techniques
2. Combination of diet and physical activity
3. Use of mobile technology
4. Analysis of and automated feedback on actual intake
5. Providing accurate nutritional information for intake tracking
6. Personalizing content to user profiles and intake history.

Research on internet-delivered personalized nutrition was done by the Food4Me project, as discussed in chapter 2. Building on the insights on personalized recommendations gained during the Food4Me study and our identified requirements and research gaps, we aim at building an intelligent nutrition assistance system provided as a mobile application. All planned features are classified and designed according to the Persuasive System Design (PSD) framework by Oinas-Kukkonen and Harjumaa (Oinas-Kukkonen and Harjumaa, 2009) (see table 14). The system provides feedback on both dietary behavior and physical activity via a mobile application. Food intake is tracked on a day to day basis and ideally soon after any food consumption. Feedback is generated automatically and delivered immediately after the given input. The feedback is personalized to the user's dietary history, phenotypic information, and measurements taken from Dried Blood Spots (DBS) samples. All nutritional content and information are either based on standards in nutrition science (e.g. the BLS food database (Hartmann et al., 2005)) or reviewed and designed by nutrition experts (e.g. feedback messages). Feedback is explained transparently to enable trust and learning. The following sections discuss how these design decisions were derived iteratively from related research and multiple design evaluations.

Table 14: Application components and their corresponding PSD elements. Table has been adapted from (Terzimehić et al., 2016).

Component	PSD element	Example in our research
Digitalization and automation of user input and dietary recommendations	Reduction	Food diary for logging daily food intake divides logging into small steps. Automation of physical activity tracking removes the task of manually logging physical activity.
	Personalization	Automated nutritional advice is personalized to user's anthropometric measures, food preferences, previous dietary intake, and blood metabolite values.
	Self-monitoring	Food diary for recording daily food intake enables the user to check upon what he/she has been eating previous days.
	Reminders	Notifications are sent if the user does not log his food in a week to get him back on track.
	Suggestion	Dietary suggestions based on several personalized criteria are being made towards healthier nutrition behavior.
Personalized recipe-based recommendations	Personalization & Suggestion	Personalized dietary suggestions are given in the form of full meal recipes.
Personalization by blood metabolite values	Personalization	Dietary suggestions are personalized, among others, to user׀s blood metabolite values.
Acceptance of dietary recommendations by explanations	Suggestion & Personalization	The recipe suggestion is accompanied by a personalized explanation on why these recipes were suggested.
Personalized visualization	Self-monitoring	Previous dietary intake is presented in graphical visuals over some time.
	Simulation	The diary shows how the health status and nutrient intake might change when food is being logged.
	Suggestion & Personalization	The opening screen shows which nutrients are not in the optimal range and suggest reducing or increasing that nutrient's intake.

The following sections review the first design cycle according to (Hevner, 2007) of our nutrition assistance system *Nutrilize*. We assess related work specific to the identified relevant design components and discuss multiple iterations of evaluation and refinements.

7.2 Related Work

7.2.1 *Personalization and Automated Feedback*

As discussed in chapter 2, the Food4Me project studies both the effects of personalized nutrition advice on behavioral changes and the creation of an automated feedback system based on usual intake from an FFQ. In their recommendations for future work, they suggest extending this approach to actual daily intake. Daily feedback is believed to partially counteract the limitations of traditional interventions such as the loss in adherence (Dombrowski et al., 2012) and difficulties in maintenance of changes in everyday life (Meister et al., 2016). One project on automated personalized nutrition with in-time feedback was done by Zeevi et al. (Zeevi et al., 2015). The authors conducted studies on the microbiome's influence and other phenotypic markers on the personal post-prandial glucose response (PPGR) to certain food items. Based on these differences, they could predict and verify the response of participants to different food items. Based on these responses, they could further recommend meals with positive response curves to the individual participants who, on a long-term perspective, might even improve their microbiome and response curves. To make such recommendations attractive for participants, they should be tailored to their health utility and their taste and preferences. One way to include these aspects in an algorithmic format is to build a content-based recommender system for recipes. This format has the benefit that multiple objectives, such as a variety of health utilities of single ingredients and a preference mapping, can be combined into one easily readable output format, i.e., a list of recommended recipes.

7.2.2 *Food Recommender Systems and Explanations*

The number of existing solutions for food recommender systems is quite small at the time of this design cycle. Early work by Freyne et al. (Freyne and Berkovsky, 2010) focusses on the transfer of utility between single ingredients and full recipes or on predicting ratings of recipes from previous user feedback (Harvey et al., 2013). Only in 2015, the first food recommender systems are starting to focus on the health aspect of nutrition. In contrast to traditional recommender systems, health-focused applications need to balance user preference with health goals that might contradict these preferences. While Ge et al. (Ge et al., 2015) Included health functions based on calories into a weighted sum of the preference and health score, Elsweiler et al. (Elsweiler and Harvey, 2015) focus on the balance of nutrition over a full week. In their state-of-the-art review on food recommender systems Trattner et al. (Trattner and Elsweiler, 2019) note that health aspects are an upcoming but not yet solved topic of food recommender systems. As already pointed out in the rigor cycle, one particular challenge derived in another state-of-the-art review on food recommender by Tran et al. (Trang Tran et al., 2018) is the provision of explanations. One work that compares different explanation strategies by Tintarev and Masthoff (Tintarev and Masthoff, 2012) focusses on how they enhance adherence. The authors show that personalized explanations can have positive effects on dropout if they provide meaningful content.

7.2.3 *Personalized Visualizations*

Personalized visualization (PV) is a sub-branch of research on information visualization (IV), which follows the promotor-inhibitor-motivation model (Sprague and Tory, 2012) by focussing on one prominent promotor, namely data that is personally relevant to the consumer. There is not much research yet on personalized visualizations of nutrition intake (Wenger et al., 2014). However, these concepts were already shown to be successful in similar contexts (Sprague and Tory, 2012). Concerning healthcare, there have been previous systems visualizing large scale datasets without the personal focus (West et al., 2014). Personalized visualization can be utilized for many essential tasks of a health application, such as self-monitoring, feedback, and planning. This design element is researched elaborately in the Ph. D. thesis of a project collaborator, Nadja Leipold.

7.3 FOCUS GROUP ON APPLICATION DESIGN REQUIREMENTS

This section shows the initial design requirements as derived from the PSD framework and the rigor cycle. This part makes frequent references to (Terzimehić et al., 2016). These components are integrated into the initial application design. This section discusses the most important aspects of the initial design and its assessment by a focus group (see also (Petrov, 2016)).

7.3.1 *Design Requirements and Refinements*

The application should cover the following components according to the rigor cycle requirements and the PSD classification: food intake tracking, physical activity assessment, automated personalized nutritional advice, notifications, recipe suggestions, intake visualization. The home screen should be designed to give immediate feedback on the user's behavior. Such immediate feedback can, for example, be achieved by a visual representation acting as a reflection-on-action mechanism (Hermsen et al., 2016). The home screen should further provide easy access to the most important and most frequent features, such as intake tracking and recommendations. The food tracking should be fast and simple to use based on the German Nutritional Database (BLS (Hartmann et al., 2005)). Recipes should further ease the input of full meals. On the recommendation screen, users should receive personalized suggestions based on phenotype, dietary history, and preferences. Additionally, these recommendations should be supported by explanations on their utility. The food preferences are collected in the form of explicit no-goes and implicit information from previous consumptions. The food diary on the left shows its usability features, such as a quick delete button and a favorite button for quick access on subsequent days. The home screen on the middle shows how the central screen is blocked for visual feedback, and both recommendations and diary are immediately accessible. The search screen on the right shows quick access to recent and favorite items as well as a search field for exploring the BLS database (Hartmann et al., 2005).

7.3.2 *Evaluation Method*

During the focus group assessment of this design, each screen was discussed in several alternate designs. The evaluation's goal was to assess design concepts with a special focus on the intake tracking components. The session was guided by eight open-ended questions structured as a discussion guide. The first question opens up a general discussion on nutrition applications and the participant's expectations. Questions 2-4 were focused on the paper prototypes and possible interactions, such as the order of screens, preference between designs, and missing features. The questions 5-7 were focused on evaluating the prototype regarding useful and motivating features, demotivating or disliked features, and wishes for further feedback screens. The final question opens a discussion on possible content, e.g., nutritional variables, displayed in the applications screens. The participants were recruited from the study program of nutrition science and biomedicine. Overall, four participants joined the focus group session for two hours.

7.3.3 *Results*

The feedback was collected and categorized into the topics application flow, application views, and additional functionality. Regarding the application flow, the selected order of screens was in line with the initial design idea. However, the participants questioned the need for a central role of the diary view. The participants preferred selecting the meals in a simple view and using the diary only for reviewing. Additionally, the users wanted to have quick access to the home screen's recommendations, especially after finishing the entry of the previous meal. Finally, the participants had general remarks on avoiding many notification or confirmation screens and avoiding any negative feedback. Regarding the design of single views, the participants had several suggestions for improvements. On the home screen, the participants requested immediate feedback on the current daily intake after each addition to the diary. The users further demanded that this feedback be tailored to their daily requirements and limits and simplified with a color palette. Finally, they wished to configure the nutrients shown in this screen, while calories and vitamins should always be visible. On the search view, the participants suggested more technical support such as autocomplete, barcode scanning, voice input, or food group based selection to avoid typing. For the food details screen, participants rejected adding a date to each entry and instead suggested automatic additions for the current date and separate interaction for late tracking. Additionally, the requested predefined size measures, such as portion, cup, and slice, to improve the amount estimation and color based feedback on nutrients while adding the food. The main input for the recommendations screen was to group recommendations by type or time and to adapt them to personal preferences. For the chart view, participants wished for information on long-term data, details on demand, and explanations on the type and functionality of nutrients. Additional functionality discussed is the support of social connections and feedback, water intake tracking, reminder photos of meals to be filled in later, user-created recipes, gamification, and visual instead of textual feedback.

7.4 USABILITY EVALUATION OF FIRST PROTOTYPE

The initial prototype implementation was refined based on the focus group results and evaluated using usability tests (see also (Petrov, 2016)). This section elaborates on the methodology and the most important findings.

7.4.1 *Prototype Refinements*

The design of the initial prototype focusses on the core component of a nutrition assistance application, namely, dietary intake tracking. Additionally, the prototype lays the infrastructure foundations, such as server communication, user profiles and login, and navigation between features. Figure 33 shows three infrastructure screens, such as the login, the home screen, including shortcuts to each meal and the recommendations screen, and the main menu.

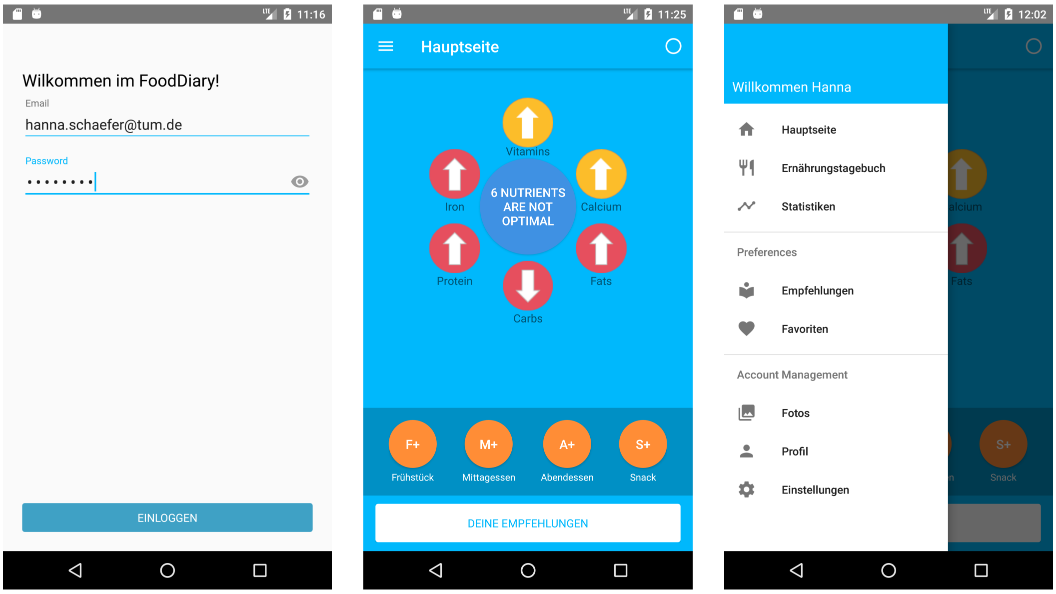


Figure 33: Login screen (left), home screen (middle), and menu (right) of the first prototype.

Concerning the intake tracking, a first search input method was implemented. Figure 34 shows the different search modes, based on recently used items, based on BLS groups, and based on a first primitive keyword search.

Each search result can be added directly from the screen with standard portion sizes, or configured to custom sizes in both the detailed food screen, the plate, and the diary (figure 35). The plate offers a concept similar to shopping carts where currently

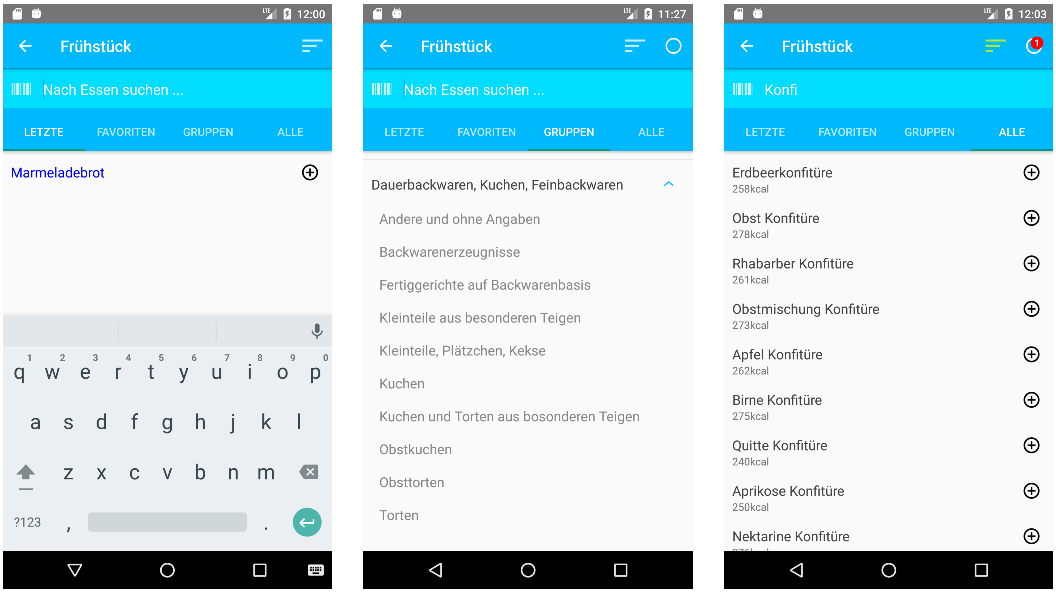


Figure 34: Search components by recent items (left), BLS groups (middle), and keyword search (right) in the first prototype.

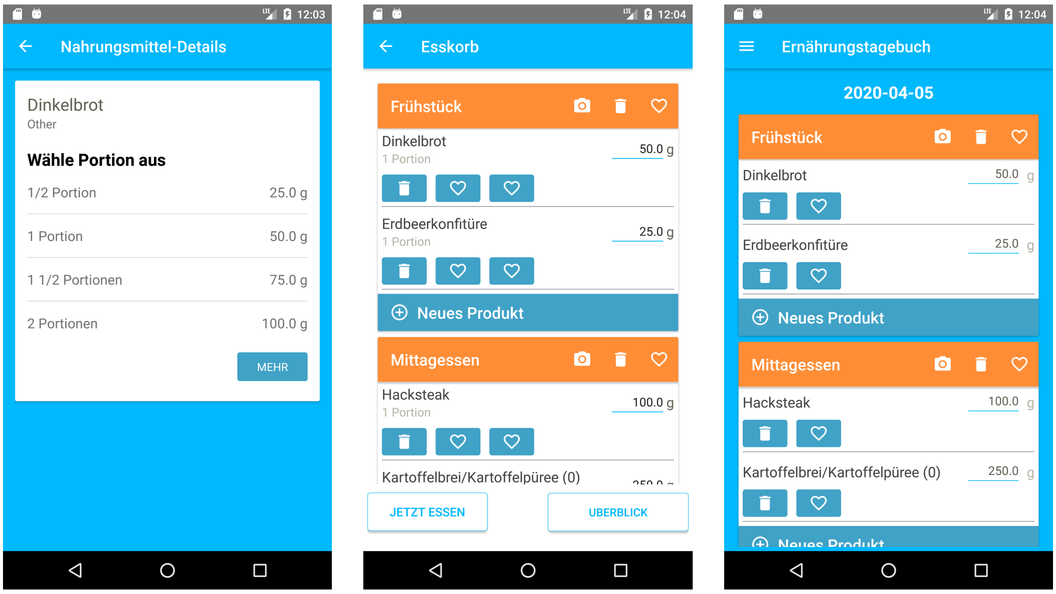


Figure 35: Food details (left), plate for a current tracking session (middle), and final diary (right) in the first prototype.

consumed items can be quickly added and configured before actually adding them to the diary.

7.4.2 *Evaluation Method*

This usability study's goals were to identify usability issues, measure the task efficiency, and retrieve feedback on the perception and future improvements of the application. The participant group was recruited from German-speaking mathematics and computer science students. Four users participated in this usability test. Each participant was invited via email and provided with background material on the test's purpose and schedule. Each test was planned in four phases, with a total of 45 minutes. The first five minutes were reserved for introduction to the study process and tasks. The next 25 minutes were reserved for solving five tasks with the prototype while thinking aloud about their experience. Both screen and audio were recorded. The posed tasks are:

1. Adding a meal
2. Editing tracked food
3. Adding forgotten past intake
4. Adding recent food item
5. Logging out

After completing all tasks, the participants had 10 minutes to fill out a survey containing the SUS questionnaire (Brooke et al., 1996). Finally, the last 5 minutes plus as much time, as participants want to spend on this phase, were reserved for an open discussion about their impression of the system and major challenges they were facing.

7.4.3 *Results*

During the study, success and timing for each task, the SUS results, and the open feedback were collected and analyzed. The success of tasks 1,2, 4, and 5 is 100%. For task three, however, two of the participants could not solve the task without outside assistance. The first task took participants the longest with an average of 105 seconds. The following tasks were solved on average in 66 (T2), 43 (T4), and 9 (T5) seconds. The variance of timings is quite high since the scenario-based tasks left much room for interpretation and exploration. The two participants who solved task 3 required 76 and 145 seconds, which again reveals issues in this task. The SUS questionnaire resulted in an average score of 76.5, with a standard deviation of 9.68. This score is very good for a first iteration prototype since even popular commercial tools only reach a maximum of 89.2 for the LifeSum application (Ferrara et al., 2019). During the open discussion, the participants gave overall positive feedback but also pointed out that there is room for improvement. The search should start on any tap on the search field instead of the search button, the group tab should be renamed to categories, and the search results should be improved. In the diary screen, they did not realize the swiping gesture was relevant, and they were missing clearer confirmations for editing actions. The quantity selector was criticized as over-complicated compared to just typing the number of grams. A number of participants requested to add past dates to the plate, which would essentially turn it into the diary screen. Finally, the icon for a plate was not recognized by all participants and thus not understood as a concept. The design of the initial prototype was extended by components for search, recommendations, and visualization. An initial idea for these additions was published in (Terzimehić et al., 2016). Each component was later revised and evaluated, which is discussed in the following sections.

Based on the initial design, the search interface for dietary tracking was extended and refined (see also (Wagner, 2016)). This section elaborates on the most important design aspects and evaluation results.

7.5.1 *Prototype Refinements*

The tracking of dietary intake is a crucial element of the *Nutrilize* application. Since methods such as image recognition and barcode matching did not deliver sufficiently accurate nutritional results, the intake tracking is search-based using the BLS database (Hartmann et al., 2005) as well as recipes consisting of BLS ingredients. Making this search as easy and efficient as possible is necessary, to decrease dropout and reduce errors in tracked dietary intake. Figure 36, left, shows the auto-completion search interface in action. By entering each letter, the interface shows an updated list of suggested elements. Additionally, ingredients can be entered as filters for recipe search results (figure 36, right). This search was implemented and refined using the elasticsearch tool. All recipes and food items are tokenized, split into composites, and stemmed. Different weighting functions have been tested for performance timings when searching for common food items. In summary, composite splits have increased the recall for searching items. Lexicon-based stemming improved the relevance of re-

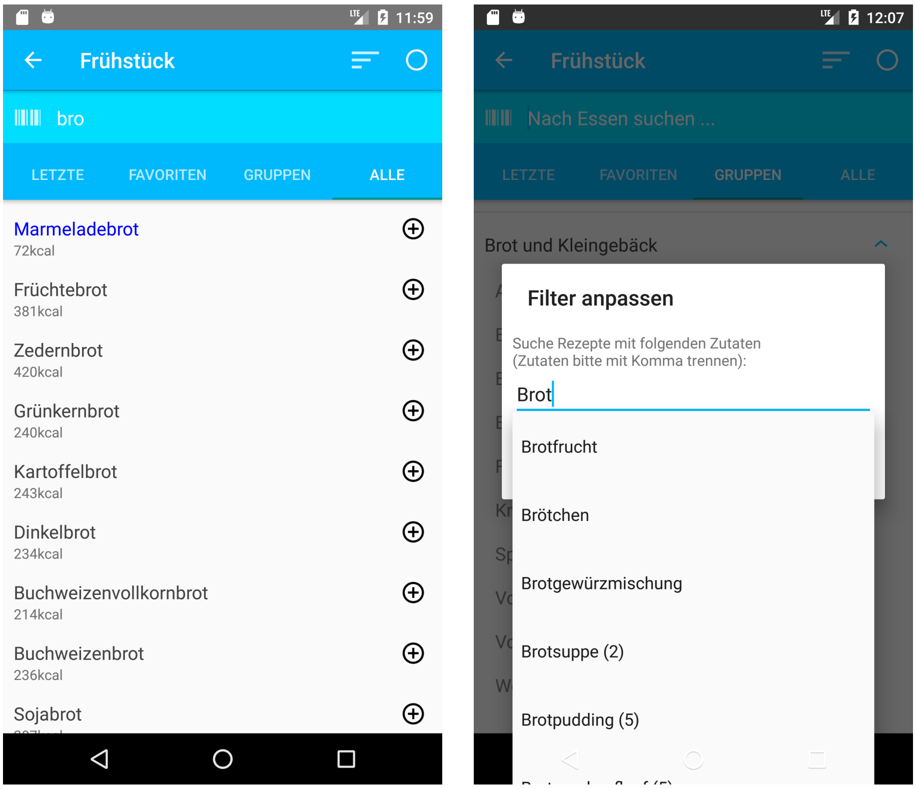


Figure 36: Search for food items and recipes in the *Nutrilize* food search screen (left) and filter for ingredients of recipes in the *Nutrilize* food search screen (right).

sults and, thus, precision. Finally, the search time was improved by optimizing the elasticsearch index structure.

7.5.2 *Evaluation Method*

The search interface was evaluated with usability-tests during the open day of the Technical University of Munich. The three main goals of the evaluation were identifying usability-issues, measurement of efficiency during tracking, and perception of the system by target users. Each participant had to one of these three scenario-based tasks:

1. Enter your favorite lunch
2. Search recipes containing four and eggs and a snack
3. Search and adapt the cheese-noodle recipe to your cooking style

Overall, 30 participants solved at least one of the three tasks. In addition to the open-day recruitment, eight participants were asked to conduct all three tasks and fill in a SUS questionnaire (Brooke et al., 1996) on the overall prototype.

7.5.3 *Results*

The observed interactions and think-aloud comments of participants showed usability issues. The most common issue was a missing understanding of the tab-dependent search field. Not all participants noted the tab for all search results and were frustrated when not finding their item in the most recent tab. After giving this hint, both search tasks were solved by 70% of participants. The adaption of recipes to one's cooking style was already solved by 50% without giving any hints. The timing of each task varied between participants. On average, users required around 2-3 minutes for the first time to solve a task. On average, the prototype reaches a usability score of 65, which is lower than the initial design and thus indicates the early stage of this feature's development. In consideration of the study results, further improvement of the interface and search algorithm is necessary. Two options are popularity-based weighting and the introduction of synonyms BLS items.

7.6 IMPROVEMENT AND EVALUATION OF RECOMMENDER COMPONENT

Based on the initial design, the recommendation interface was extended and refined (see also (Frenzel, 2017)). This section elaborates on the most important design aspects and evaluation results.

7.6.1 *Prototype Refinements*

The recommender interface (figure 37) is split by meal type (breakfast, lunch, dinner). In each tab, a ranked list of recipes is shown with its title and picture. Each recipe is additionally color-coded by its health utility according to the recommendation algorithm. Users can optionally switch to an image only view with key indicators on each recipe (calories, fat, protein, carbohydrate) overlaying the picture. In this case, not the title, but the image frame show the color-coded utility value.

Figure 37: Recommender system interface as a ranked list (left) or table of images (right).

To get a quick insight into the recipe, users can select the ingredient list or cooking steps of each recipe (figure 38).

For further details, they can click on the title or image of the recipe and see the recipe details screen. In the recipe details screen, they see the image, ingredients, and steps. Users can further select a portion size to eat, and it is automatically added to their food diary. Finally, the recommendations can be filtered by keywords or ingredients to allow quick access to healthy recipes that fit the user's fridge content (figure 39).

7.6.2 *Evaluation Method*

The design of the recommender interface was evaluated regarding its usability in a user test with nine participants. Each participant received five tasks to solve in the applications. The tasks are provided as small scenarios leaving lots of freedom for exploration. All interactions with the system were observed regarding problems and holdbacks. After solving all tasks, the participants were interviewed on their impression of the system. The interview was semi-structured and focused on positive and negative impressions as well as suggestions and improvements. The participants

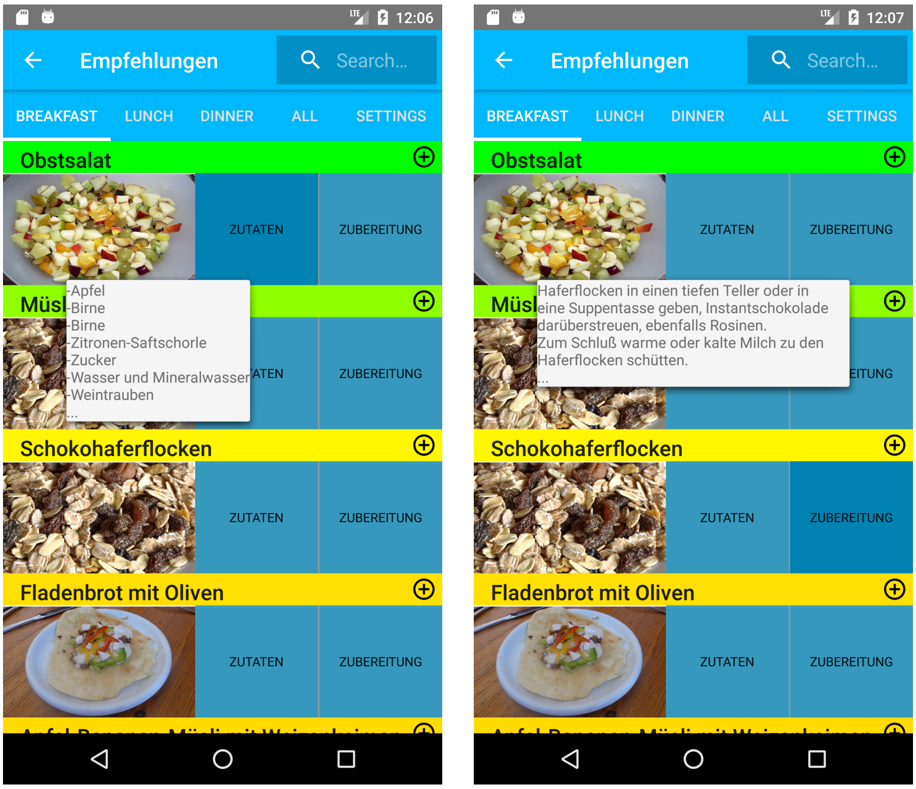


Figure 38: Details on ingredients (left) and cooking steps (right) for each recipe in the recommendation list.

were between 20 and 24 years old. Eight of the nine participants were male, and five were students in a computer science program.

7.6.3 *Results*

The review of all nine user-tests resulted in three main insights. First, three of the users could not configure the recommendations and thus only used half of the design space. Second, users did not understand how to add recommended recipes directly to their diary. Finally, the keyboard obscures larges parts of the screen during the search activity, which made an in-action review of more than three search results impossible. As a follow-up, the interface was updated with hiding the keyboard on interactions with the list, adding plus buttons to each recipe entry, and externalizing the setting to a separate tab, which automatically updates all other tabs.

7.7 IMPROVEMENT AND EVALUATION OF VISUALIZATION COMPONENT

Based on the initial design, the visualization interfaces were extended and refined by an interdisciplinary project advised by my colleague Nadja Leipold (Moyon et al., 2017). This section elaborates on the most important results.

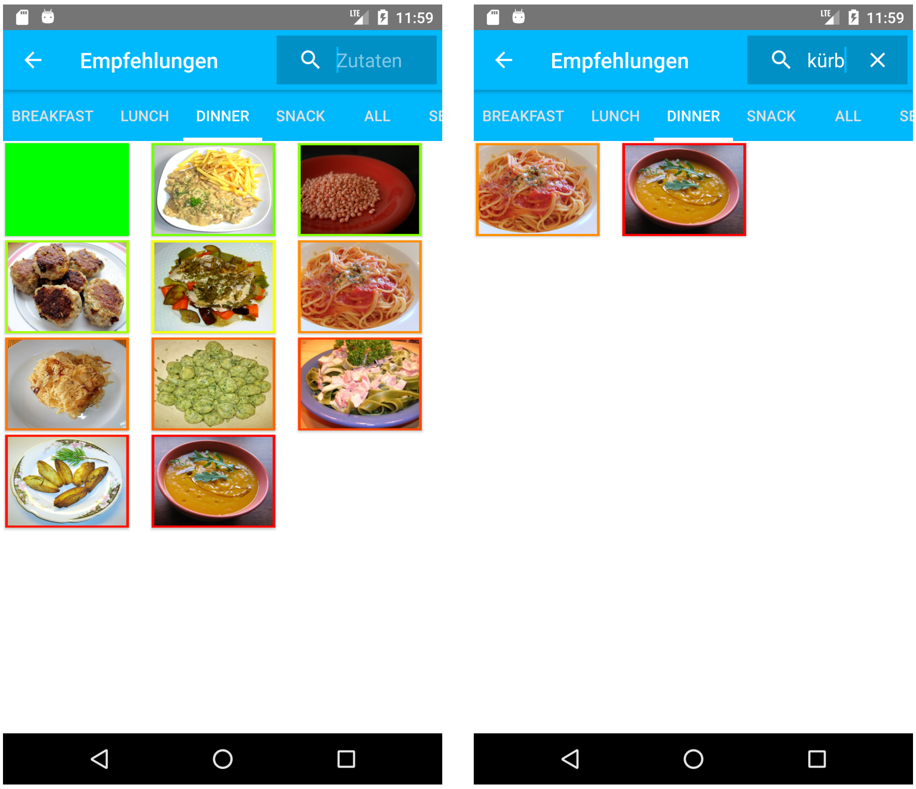


Figure 39: Filtering of recipes according to keywords and ingredients.

7.7.1 *Prototype Refinements*

The visualizations are grouped according to the time frame of data they visualize. The home screen shows data on the six most critical nutrients of the past three days, excluding the current day (figure 40). The arrows indicate intake actions the user should take (increase, decrease, maintain) and the colors the current state of a nutrient (green=optimal, yellow=suboptimal, red=very suboptimal). When clicking the summary circle on the home screen stating how many nutrients are in critical states, a list of all nutrients and their current state is shown on the nutrient status screen (figure 40). In addition to the consistent color coding, this view enables the users to see their specific state on the scale and the values associated with neighboring target states. Additional information on each nutrient is provided when clicking on it either on the home screen or in the nutrient status screen. This nutrient details screen provides the intake values of the past three days and textual information on the effects of this nutrient, possible food items that contain it, and the dietary guidelines the evaluation is based on (figure 40). These three screens aim to provide feedback on current behavior and future improvements to the user.

Other visual components focus on the past history of intake in either calories (figure 41) or nutrients (figure 41). The calorie overview shows the intake and burning of calories over the past week, including the current day. The calorie bar indicates how many basic calories are available, how many bonus calories were earned by physical activity, and how many calories were consumed on each day. The statistics screens

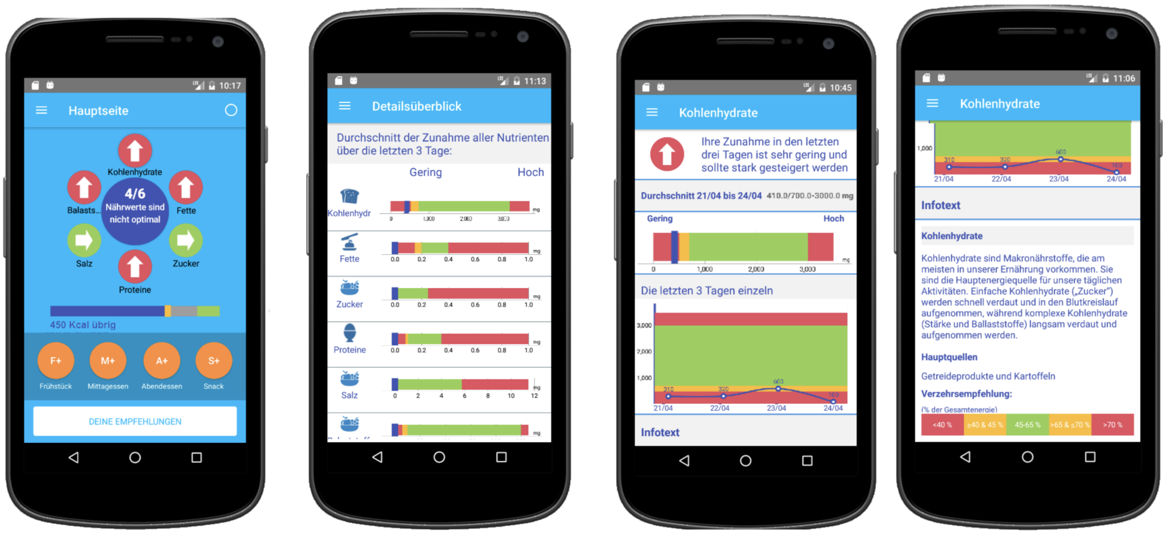


Figure 40: Visual components from left to right: Home screen, nutrient status screen, nutrient details screen top, nutrient details screen bottom. These figures have been taken from (Moyon et al., 2017).

show the history of nutritional intake over the current day, week or month. The color coding is coherent in all nutrient views.

Figure 41: Visual components from left to right: Calorie overview screen, statistics screen day, statistics screen week, statistics screen month. These figures have been taken from (Moyon et al., 2017).

7.7.2 *Evaluation Method*

The visual design was evaluated during the open-door day at the Technical University of Munich. Forty participants were interviewed regarding the usability and understandability of the visual components. The open-door day, provided access to a diverse set of visitors. The participants' ages range from 15 to 50 years. Each participant was interviewed in the following manner:

1. Explain the applications goals and the project background
2. Retrieve feedback on the understanding and opinion of each visual components
3. Explain possible interpretation errors
4. Ask for opinions and future improvements
5. Ask general feedback

7.7.3 *Results*

The notes form all interviews were clustered according to screens and reviewed for common feedback patterns. Due to the evaluation's open situation, not all participants gave equally detailed feedback to all screens. The most challenging screen, judging from the mistakes in interpretation, is the home screen. The color coding and arrows lead to different assumptions in the user's minds. For example, the reference time was not stated clearly, and the arrows' interpretation as either the current state or the future direction was unclear. The nutrient status and details screens were understood very well, and the statistics screen, while at first overwhelming, was also understood quickly after feedback. A subset of participants (13) also gave input on the general-purpose and effectivity of these visualizations. Most of them believed that this application could help influence their eating behavior. A number of participants named quick dropout and information overload due to too complex data as feedback.

7.8 IMPROVEMENT AND EVALUATION OF SOCIAL COMPONENT

As discussed within the rigor cycle (chapter 2), social exchange is a significant motivator for long-term engagement in behavior change applications. The reviewed commercial applications all solve this feature with a social platform that allows exchange on progress and personal stories. Some offer a public platform, and others exchange with friends only. In our socio-technical system for games (chapter 3, we have provided this aspect in the form of matched groups that play social games together and can communicate with each other both virtually and in persons. In the socio-technical system for adults designed in the current chapter, we took inspiration from another successful application called the Eatery App (Helander et al., 2014, Turner-McGrievy et al., 2015). In this application, users can post pictures of their dietary intake and receive ratings from the other users. This approach covers three central elements from the rigor cycle, which we will address in the subsequent design description, namely social exchange, picture-based dietary tracking, and rating-based utility estimation. To decide on the feasibility of such a design, we investigated different aspects of the picture rating process (see also (Liu, 2016)) and its accuracy. We further evaluated the system's motivational elements, including social exchange, recommendations, and gamification (see also (Ezzeldin, 2016, Polácek, 2017)). The subsequent section will present the design choices and their initial evaluation insights.

Concerning the rating-based utility functions, we investigated the usability of different rating interfaces and the accuracy of health-based ratings estimated by both novices and experts. Based on feedback during initial user tests (see also (Liu, 2016)), we decided to use sliders with predetermined step sizes for the rating procedure. The final rating interface is shown in figure 42 in the middle. The interface focuses on the two categories health and taste as a basis for user feedback. Further, it offers to estimate different nutrients as well as the calorie content of a picture. The pictures and their ratings are presented to other users in a stream, similar to commercial social media apps (see figure 42 left). Additionally, users can see their own dietary diaries in their profile view (see figure 42 right). The overall design of this picture based diet tracking and social sharing feature is derived from posting streams in social media such as Instagram or Facebook. The stream can be extended to support some of the other design components, such as offering a stream of recommended meals or giving visual feedback on the ratings received.

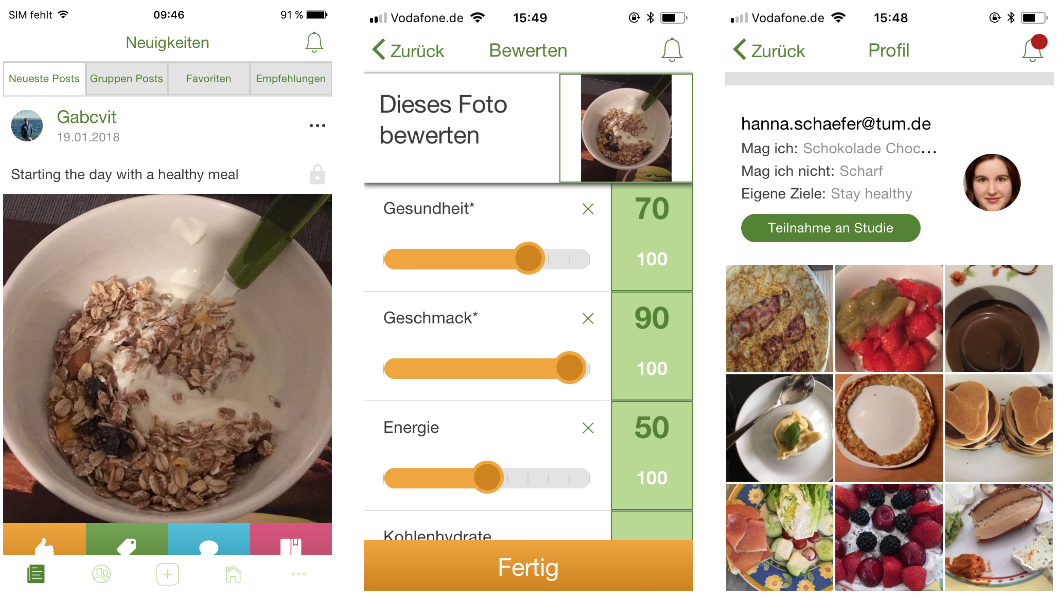


Figure 42: Picture-based dietary tracking with a stream of posts (left), crowd-based ratings (middle), and a history of posts in the user's profile (right).

This kind of visual rating feedback is presented in the form of a calendar heatmap. Here users can see how healthy their intake was over time according to the crowd's estimation (see figure 43 left). Since the effectiveness of such a measure depends heavily on the continued rating provision by other users, we additionally added theme-based or private social groupings (see figure 43 middle) and trophies for different in-app actions (see figure 43 right). The social context provides an incentive to review and rate the postings of friends or likeminded people. This way, the users can also avoid listings of uninteresting posts on their timeline. On the other hand, the trophies support activities such as the number of posts provided, the number of groups joined, and, most importantly, the number of ratings. It furthermore can be extended by health goals such as achieve an average rating higher than 3.0 on seven consecutive days.

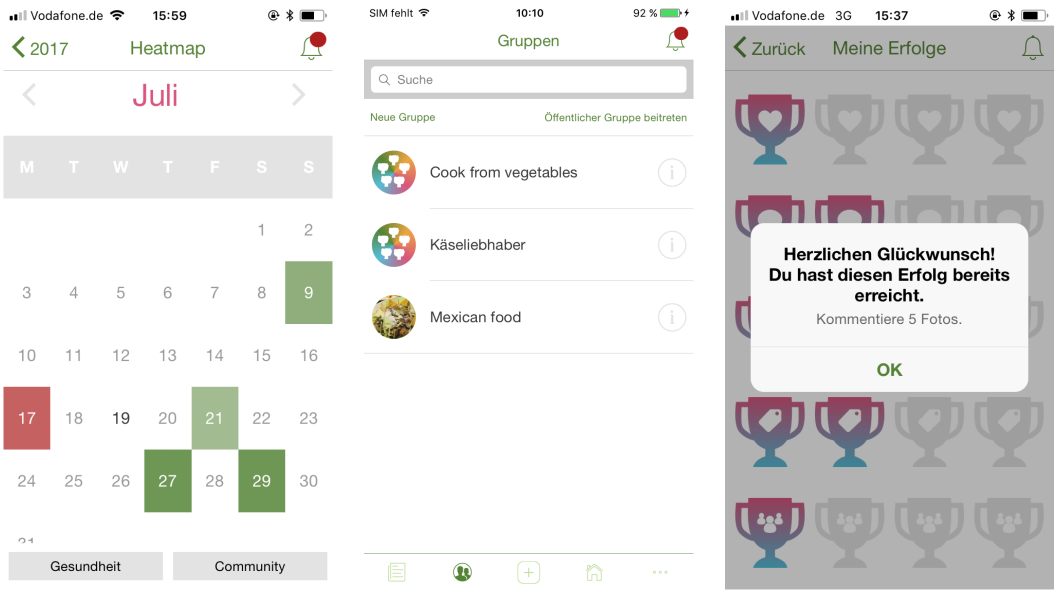


Figure 43: Motivational elements of the application such as a heatmap of the crowd based ratings received (left), a flexible system of public and private groups for different interests (middle), and a trophy system nudging users to stay active in the applications(right).

7.8.2 *Evaluation Method*

To investigate the accuracy of crowd-based health ratings, we surveyed 110 experts and 233 non-experts on their rating abilities. Each participant was asked to rate the calories, carbohydrates, sugar, and fat of a random selection of six food images. The results were compared with ground-truth values on the nutritional content of each meal. We conducted a user study with 10 participants over ten days (see also (Polácek, 2017)). The participants were asked for their expectations of the system before seeing the application. During ten days, we tracked their activities in entering and rating food pictures. After the interaction phase, they were asked to give feedback on the usability, the motivational aspects, and the general impression of the system.

7.8.3 *Results*

The survey on rating quality in experts and non-experts provided important insights into the feasibility of crowd-based utility estimation. Experts showed an overestimation for all nutrients by 4-11%. Non-experts, on the other hand, reached an overestimation of 10-28% for all nutrients except carbohydrate, which they instead underestimated. For sugar and carbohydrates, the difference in ratings between experts and non-experts was significant. For calories and fat, it was not. We conclude that while a crowd-based rating might be a feasible alternative to more detailed tracking options, it does not provide sufficient accuracy to be used for personalized feedback.

The user study revealed several insights into the usability and motivational effect of our design. Seven out of the ten participants perceive the application to be able to change their dietary behavior. The average SUS score (Brooke et al., 1996) was 71, which indicated a good usability. Within the social exchange system, participants joined two groups on average. While the groups were generally perceived as useful, the participants expected more features connected to them. This disappointment might be due to the prototypical state of the application. Further, users perceived their groups as collaborative but not as competitive towards other groups. The calendar heatmap of received ratings was not perceived as motivating by the users, although they did enjoy the ratings themselves and most provided ratings daily. On the other hand, the trophies were accepted and liked by most users and provided their intended impact on increased system usage over time. Overall, users were demotivated by the prototype's preliminary state, but they enjoyed the trophies, ratings, and picture postings. Finally, the participants wished for more photo editing tools, like buttons, and other features similar to commercial social platforms.

While the initial feedback on this social design component was very positive, the targeted user group differs from that of the *Nutrilize* application. In the *Nutrilize* case, we insist on using the BLS database because we consider other more convenient databases to be less accurate while in the crowd-sourced case, we would be accepting high error rates. Also, the *Nutrilize* features such as personalized feedback and tailored recommendations, rely on the detailed tracking information. As discussed in the rigor cycle, picture-based estimation of nutrition is still far from optimal. Users who favor a quick and easy picture-based social exchange would likely be discouraged from additional detailed tracking. These discrepancies in target user groups lead to integrating the social and rating based design components into a separate application called *Appetite*. A thorough evaluation of this application will be conducted outside the scope of this thesis. The subsequent secondary design cycles and both relevance cycles will focus on the *Nutrilize* system without the social component.

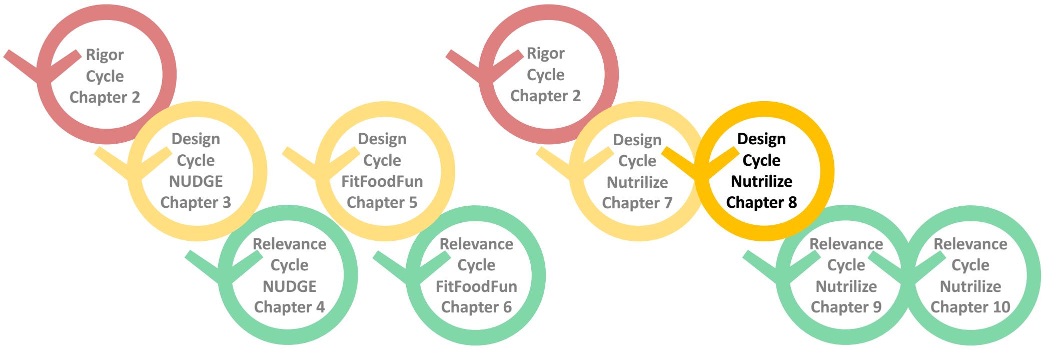
7.9 Conclusion and next steps

This chapter has covered the first design cycle, including the derivation of components based on the rigor cycle, focus groups on the initial prototype design, and user tests for single components. Following this process, there is a need for a second design cycle that incorporates all previously collected feedback. This complete prototype is evaluated regarding its holistic experience and its effects on user behavior. This second design cycle is discussed in the following chapter.

The *Nutrilize* nutrition assistance system is designed to provide support in behavior change of adults. The main components selected and designed in this chapter are a dietary diary assessing the user's nutritional history, a recipe recommender system for different meals personalized by the user's phenotype and nutritional history, and a visual feedback system for both retrospective reflection and proactive guidance. The additionally designed social component is not continued in the combined prototype, but will instead be regarded in a separate application called *Appetite* outside of the scope of this thesis. After reviewing relevant literature on each of these aspects and the general requirements derived in (chapter 2), each component was designed refined and evaluated in this design cycle. While the individual components were perceived as useful during their evaluations, the feedback revealed issues of usability and understandability that were remedied respectively. As a next step, the interplay of these components needs to be redesigned and evaluated. This second design cycle is discussed in the subsequent chapter.

8

PILOT STUDY ON A NUTRITION ASSISTANCE SYSTEM



The components of the *Nutrilize* system designed in the previous design cycle were perceived well in individual user tests. However, there is a need to design and reiterate the overall system and the interplay of these components. Longer interaction sequences need to be considered to gain insights into this interplay between the design components. This chapter elaborates on a pilot study testing the usage patterns and perception of the *Nutrilize* system. After iteratively designing and refining all components of the *Nutrilize* application, the second design cycle covers a pilot study on the complete prototype over 21 days considering data from 14 participants. The design of the entire prototype has been refined and adapted before the pilot study. Especially the algorithmic design has been optimized and reviewed by nutrition experts. The final pilot prototype and algorithm are described in the following sections. The study results were previously published in a workshop paper at the HealthRecSys workshop in 2018, and a few paragraphs make frequent references to this publication of the pilot study in (Leipold et al., 2018). The evaluation focuses specifically on the mixture of usage between the offered features, the impact of real-life nutritional input on the system, and the overall usability perception.

8.1 MOTIVATION

As derived during the rigor cycle (chapter 2), many applications target population-based guidelines for healthier nutrition. In contrast, the personalized nutrition assistance system *Nutrilize*, designed in the previous design cycle, provides personalized feedback based on the user's phenotype, nutritional history, and individual preferences. This chapter describes the holistic *Nutrilize* system and its underlying algorithmic structures after designing multiple persuasive components. The algorithm is dependent on the input of the designed dietary diary and feeds its output into the tailored recipe recommendations and visual feedback. It aims to support the following of the initially derived requirements:

1. Combination of diet and physical activity
2. Analysis of and automated feedback on actual intake
3. Providing accurate nutritional information for intake tracking
4. Personalizing content to user profiles and intake history.
5. Explaining provided feedback to enhance trust and empowerment

To validate the suitability of both the algorithmic system and the combined nutrition assistance application, we conduct a pilot study over 21 days with 14 participants. We focus our analysis on the intake tracked in real-life settings, the interactions done by real users, and the feedback on perception and improvements of the applications.

8.2 ALGORITHMIC DESIGN CYCLE

Similar to the interface design, the algorithmic design underlying to all interface components was reviewed and improved in multiple iterations.

8.2.1 *Initial Algorithmic Design*

The first algorithmic design was developed in collaboration between the computer science department and the department of nutrition science (see also (Hecktor, 2015), (Greupner, 2015)). As discussed in the rigor cycle, formal nutrition models need to cover the user profile, food information, and utility functions. The user profile variables that were considered are:

1. the BMI calculated from the user's height and current weight

2. the waist to hip ration calculated from the hip-measurement and waist measurement

3. the user's basal metabolic rate calculated from age and gender

4. the total energy expenditure calculated from the physical activity level and basal metabolic rate

5. the user's risk for diseases based on the families' disease history concerning hypertension, Type 2 Diabetis Mellitus (T2DM), dyslipidemia, and cancer

The variables from the user profile are later used to weight different nutrients in a personalized way. The food diary builds a bridge between pure food or pure user-related information. To consider previous dietary intake is a crucial part of the personalization. Regarding the information on food items, two types of input need to be distinguished. Single ingredients such as an apple are retrieved from the BLS database (Hartmann et al., 2005), where all nutritional values and information on the items food group are stored. Recipes can be crawled from different online sources, but need to be matched to the BLS database to extract their nutritional values (Müller et al., 2012). The advice or utility functions used in the *Nutrilize* system (see also (Hecktor, 2015)) were provided by comparison across multiple nutritional guidelines by (Greupner, 2015). The general idea of the utility functions is to map the previous intake of nutrients to a value range from 1 (strong increase) via 0 (maintain) to

-1 (strong decrease). The calculation comprises four core components: intake vector, weighted advice vector, recipe utility vector, and the final ranking. The intake vector is calculated by averaging the consumed amount of each nutrient over the past three days. Additionally, the amount of intake from each food group was accumulated in the same way. For each intake measure in this vector, personalized advice function is applied to map the values to a range from -1 to 1. The advice is personalized by gender and age. The advice values are weighted for a number of nutrients stronger based on the groups of users derived from the other profile variables. Users that are in multiple groups receive the average weighting of these groups. The recipe utility vector represents the contribution of a recipe to each nutrient advice. The utility is calculated by multiplying the recipe's nutrient and food group vector with the user's weighted advice vector. The recipes' content is not normalized by weight, so recipes with similar profiles but higher amounts would result in higher ratings. The final rating is based on the sum of recipe utility values. Rankings are based on descending order of ratings split between meal types. This initial algorithm's limitations are the trade-off between positive and negative nutrients when summing up all utilities, the limited number of test recipes for validation, and the missing explanation component. Finally, the ranking should ideally be based on the user's health and include a taste preference component. The subsequent two sections elaborate on how we addressed these limitations.

8.2.2 *Refinement of Algorithmic Design*

The recommender algorithm was reviewed, tested and refined in collaboration with nutrition science experts in multiple iterations. Significant changes include the removal of food group evaluation, the addition of DRI and DACH reference values, the update of group-based weighting schemas, the addition of blood values, the deletion of family disease history, the addition of weighted sums for the overall recipe utility, and the addition of explanations. The most critical decision for accurate nutritional

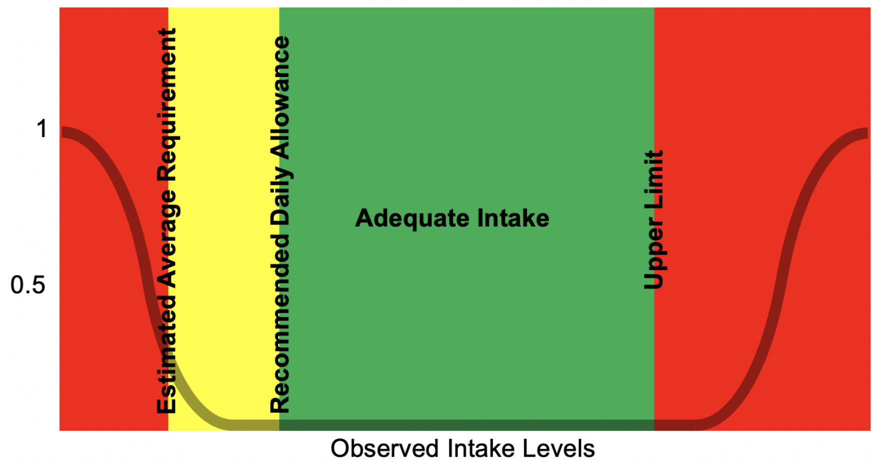


Figure 44: Nutrient response curve of the DRI concept. Adapted from (Otten et al., 2006).

feedback is the choice of a nutritional database. Between the popular options BLS, FDDB, and FatSecret, only the BLS (Hartmann et al., 2005) offered sufficient types of nutrients and adequate accuracy. During the pilot study, 26 of the nutrients provided by the BLS were retrieved and evaluated. Although included in the BLS database, the intake of food groups was removed due to the missing validation of the available advice functions. The user profile was also refined. The family history of diseases was excluded, and instead, blood measurements were used to group users. BMI, Waist-Hip-Ratio (WHR), gender, and age remain in the user profile to personalize the advice. While BMI and WHR influence the portion sizes recommended, gender and age are parameters in the advice functions. The advice functions are based on the DRI from the Institute of Medicine (of Medicine (US) Subcommittee on Interpretation and of Dietary Reference Intakes; Institute of Medicine (US) Standing Committee on the Scientific Evaluation of Dietary Reference Intakes, 2000) and the D-A-CH reference values (für Ernährung Österreichische Gesellschaft für Ernährung Schweizerische Gesellschaft für Ernährungsforschung Schweizerische Vereinigung für Ernährung), 2008). Figure 44 shows the DRI curve. For the classification to values between -1 and 1, the DRI curve is split into five areas. Any intake below the Estimated Average Requirement (EAR) is mapped to 1 for a strong increase. Intake above the Upper Limit (UL) is mapped to -1 for a strong decrease. All other values are mapped in a continuous way around the optimal intake (0 maintain) between intakes between EAR and Recommended Daily Allowance (RDA). The final set of recipes is obtained from the KochWiki (Koch-Wiki, 2019), which is licensed under Creative Commons Attribution - ShareAlike 3.0 (Creative Commons, 2020). The 240 recipes used in the pilot version of the application were matched to the BLS with an adapted version of (Müller et al., 2012). The overall recipe utility was not linearly summed up, like in our initial algorithm. Instead, according to past intake, the most critical nutrients are weighted higher than nutrients with almost optimal intake. Finally, the algorithm was used to generate explanations for each recommended recipe based on the most influential nutrient in this recipe's final rating. The explanation texts were handcrafted by collaborating nutrition experts from the *enable* project (enable cluster, 2020) and emphasized positive attributes of the respective nutrient.

8.2.3 *Extension of Algorithmic Design*

One of the significant limitations of both the initial and refined algorithms is the missing information on user preferences. Since the user already has a high task load, asking for ratings might further decrease engagement and adherence. Thus, we built an algorithm to derive preferences from past consumption patterns (see also (Ramirez, 2017)). This section elaborates on critical algorithmic aspects and results from the evaluations. The recommendation strategies are based on the user's intake tracking over the past seven days, separated by meals. For instance, if a user always eats strawberry yogurt for breakfast, the algorithm would rank breakfast recipes with fruit and milk products higher. All food items in the BLS and all recipe ingredients have a BLS identifier. This identifier indicates the type of food items with 20 main categories, such as "bread", and ten subcategories such as "tropical fruits". The items in a user's food diary are aggregated by their category or subcategory and weighted according to their frequency over the past seven days. The recipe rating from 1 to 5 is predicted according to its ingredients. Depending on whether categories or subcategories are used as an aggregation measure, or whether meals split aggregation, the algorithm produces different outputs.

The overall performance of these approaches was evaluated in offline tests and user studies: The initial offline experiment was conducted with 38 overlapping ratings from 6 users on 22 recipes chosen at random from a total set of 171 recipes. A set of seven standard algorithms was evaluated with Normalized Discounted Cumulative Gain (NDCG) and Mean Average Precision (MAP) acting as comparative evaluation metrics according to (Said and Bellogín, 2014). The best performance in NDCG was achieved with a implicit matrix factorization method by Hu, Koren, and Volinsky (HKV) (Hu et al., 2008). The user-based algorithm shows the worst performance, due to its sensitivity to the given dataset. For the first user study, 13 users rated a subset of 50 recipes from a total set of 171 recipes. The participants' task was to simulate ratings from a 29-year old male, of which they had a 7-day diary. The participants were eight women and five men aged between 20 and 60. This evaluation aimed to see whether a diary-based rating prediction would show similar results to average user-generated ratings. All except the subcategory-meal strategy showed a high overlap between the top 6-8 recipes from the ratings and the diary-based list. Due to the artificial situation of simulating ratings from a diary, the second user study focussed on diaries and ratings from the same person. The study collected more than 100 ratings from each of the three participants on 240 recipes. The same three participants were asked to fill in their food diary for seven days. The resulting top three rankings for four meal types from both diary-based strategies and the best three standard rating-based algorithms were shown to the three users for evaluation. In general, users preferred category-based methods over subcategories. Also, splitting the analysis by meal gave better recommendations in combination with categories than not splitting. This result is in line with results from the initial offline experiment. Overall, the users preferred the diary-based lists to the standard algorithms, with HKV again being the best performing algorithm.

8.3 PROPOSED SOLUTION

The interface design has been revised according to the feedback collected in each of the studies discussed in chapter 7. The following section discusses the reasoning for final prototype changes and the observations of a large pilot user study. The system consists of three components for intake tracking, recommendations, and visual feedback.

8.3.1 *Intake Tracking*

The intake tracking features are shown in figure 45. Compared to the initial design, several components have been updated. The largest change is the removal of the plate component. Each of the four meals can now be accessed directly via the home screen. When adding a food item via the search or food details, it is directly added to the food diary. For quickly adding many food items, the search provides a plus button. Portion sized can be changed in the diary, or food details screen by updating the weight text field. Additionally, the food-details screen already provides default portion sizes according to the BLS. In addition to the initial search, a group based search, and a recent items search have been implemented, and the ingredient-based search is not part of the regular search text, instead of a separate screen. Finally, a new component has been added to the overall design, which includes the tracking of physical activity levels by filling in a standardized Norman questionnaire (Norman et al., 2001). This feature can be accessed via the home screen.

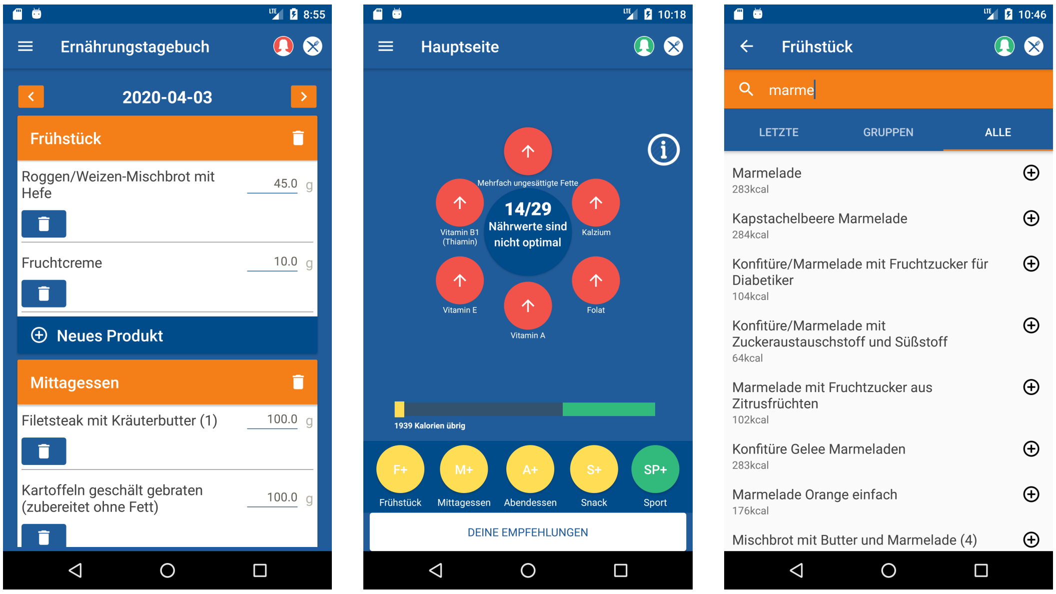


Figure 45: Tracking features of the pilot study prototype: Diary screen (left), home screen (middle) and food search (right).

8.3.2 *Recommender System*

Apart from the algorithmic updates discussed in section 8.2, the interface of the recommender system was updated, as shown in figure 46. The image, ingredients, and cooking steps are now part of the recipe details screen. Instead, the overview of the ranked list transparently shows the recipe's explanation when clicking the button next to the recipe image. The color-coding does not represent the recipe's overall ranking anymore, but only the health rating. This color coding might lead to yellow recipes above green ones if the user's preferences are considered. The value of the recommended portion size is another new feature which is based on the users calorie requirements tailored to their Basal Metabolic Rate (BMR), Total Energy Expenditure (TEE), BMI, and WHR.

8.3.3 *Visual Feedback*

The new design of the visual feedback components is shown in figure 47. The color scheme of the complete app has been redesigned. The color-coding of the feedback is thus adapted to fit the overall design. All feedback is still given with traffic light

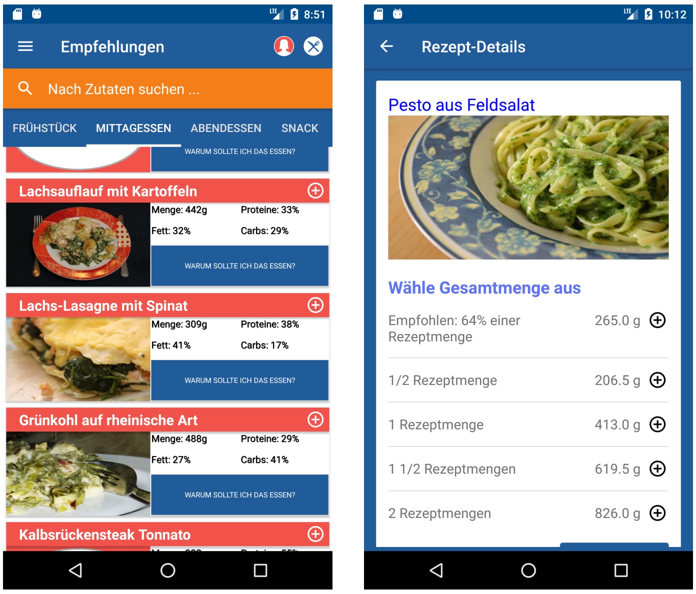


Figure 46: Recommender features of the pilot study prototype: Recommendation list (left) and recipe screen (right).

colors, which are already clearly associated with feedback for most users (Brown, 1998). The daily overview split by meals has been removed in the statistics screen due to a risk of misinterpretation.

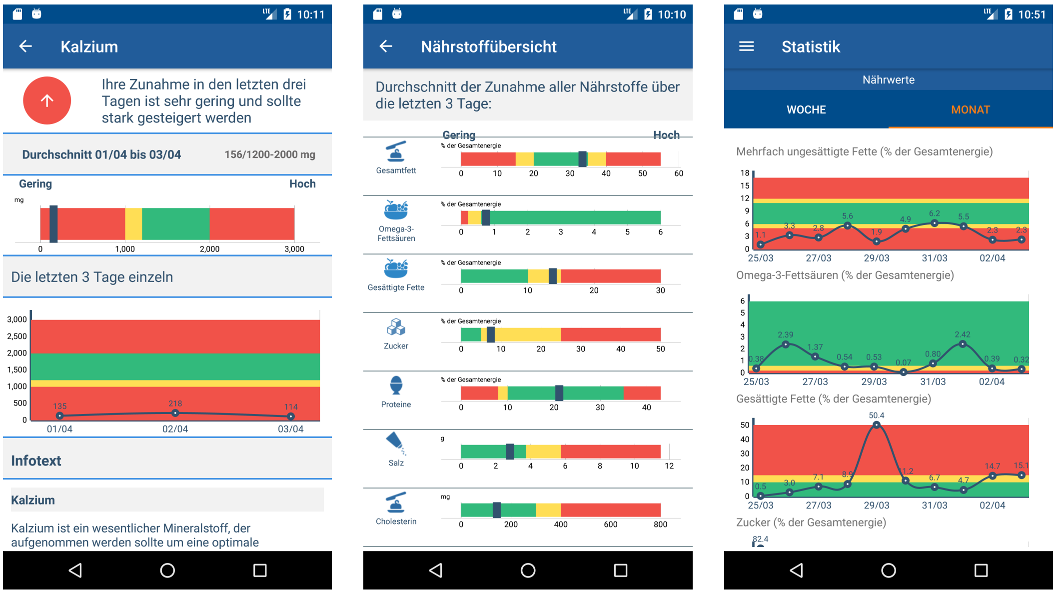


Figure 47: Visualization features of the pilot study prototype: Nutrient details screen (left), nutrient overview (middle) and statistics overview (right).

8.4 Evaluation

This is a proof-of-concept study focused on the design and usability of the application. While pre- and post-tests for a within-subject comparison were conducted, they are not expected to show significant differences. The TUM ethics committee approved the study (no. 477/16 S). Some results of this study have been published in our paper (Leipold et al., 2018).

8.4.1 *Study Procedure and Participants*

Twenty participants evaluated the new prototype of the *Nutrilize* system over three weeks. Of the initial 120 invitations, sent to the *enable* research participation database (enable cluster, 2020), only 31 participants filled out the screening survey. Twenty of these participants were fit to use the app according to medical, technical, and ethical checks conducted during the screening. None of the participants received monetary incentives. As part of the study, participants had to fill out a survey before and after using the application for three weeks.

8.4.2 *Data Collection*

The survey contained a food frequency questionnaire, a Norman questionnaire (Norman et al., 2001), height, weight, waist, and hip circumference. The pre-study survey also asked about the background, cooking habits, health attitude, and technology trust. The post-study survey asked additional questions on the usability using a System Usability Scale (SUS) questionnaire (Brooke et al., 1996) and specific feedback for each application feature. During the application usage, the participants received a manual of the system and were tracked regarding their daily intake and their interactions with the mobile application using a tracking tool named Matomo (Matomo, 2020). Only 14 participants fulfilled all measurements take and are thus included in the evaluation.

8.4.3 *Results*

The group of participants consists of six male and eight female participants between 23 and 65 years old. Both the low female gender bias and the high average age of 45 are surprising. The average BMI is slightly over the limit of 25 for overweight. The participants tracked their dietary intake using the application on average on 17 of the 21 days, but at least one participant did not enter any food items. A similar distinction between users is visible for other activities within the application. The most active user spent 14 times as much time with the application as the least active one. The average visit count of 77 for the average number of 17 diary entries indicates around four visits per day, which corresponds well with the four meals tracked in the application. All characteristics are summarized in table 15.

Figure 48 and 49 show the distribution of feature usage among different participants. The interactions with intake tracking (around 85%) were excluded from this visualization. Besides user 2, most emphasize visual feedback and focus less on the

Table 15: User characteristics of 14 participants and their application usage.

	Age	BMI	Avg Calories per Meal	Day of Last Food Entry	Time Spent	Actions Done	Recommendations Accepted	Visit Count
Min	23.0	18.4	0.0	0.0	5432.0	327.0	1.0	11.0
Max	65.0	36.1	288.8	21.0	78012.0	8808.0	109.0	192.0
Average	44.5	26.6	156.2	17.4	32157.8	5176.3	45.9	77.1

given recommendations. This impression is further confirmed in the feedback given during the final survey. The recommendations were criticized for lack of diversity and the difficulty of cooking the recipes. Overall the application received a SUS score (Brooke et al., 1996) of 52, which is below the results that single components received during the pre-studies. Besides this low score for the readiness, the application was still perceived well as a concept, with 43% of users starting to want to use the system frequently. The users perceived the nutrient visualizations and the recommendation explanations as helpful but would prefer an FFQ based tracking method to the daily intake tracking. For future modifications of the system, the participants suggested improving the intake tracking, adding more differentiated sports tracking, adding more recipes, and giving more positive feedback. Regarding the total use of features (figure 49), we observe a strong focus on the calorie feature, which is mostly contributed to by three participants. The other feature interactions were spread more homogeneously among the participants.

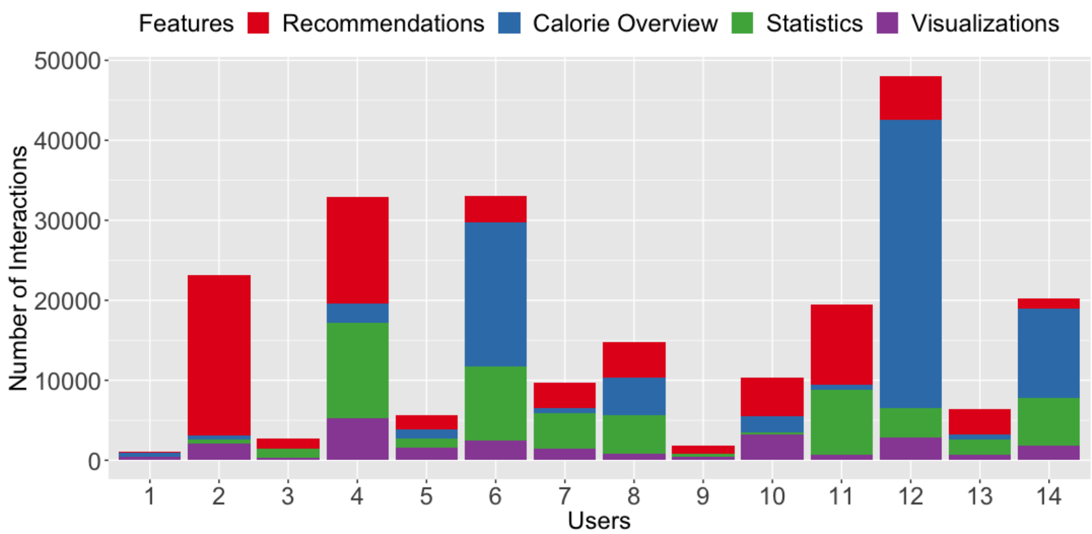


Figure 48: Number of interactions per user with screen type as color-coding.

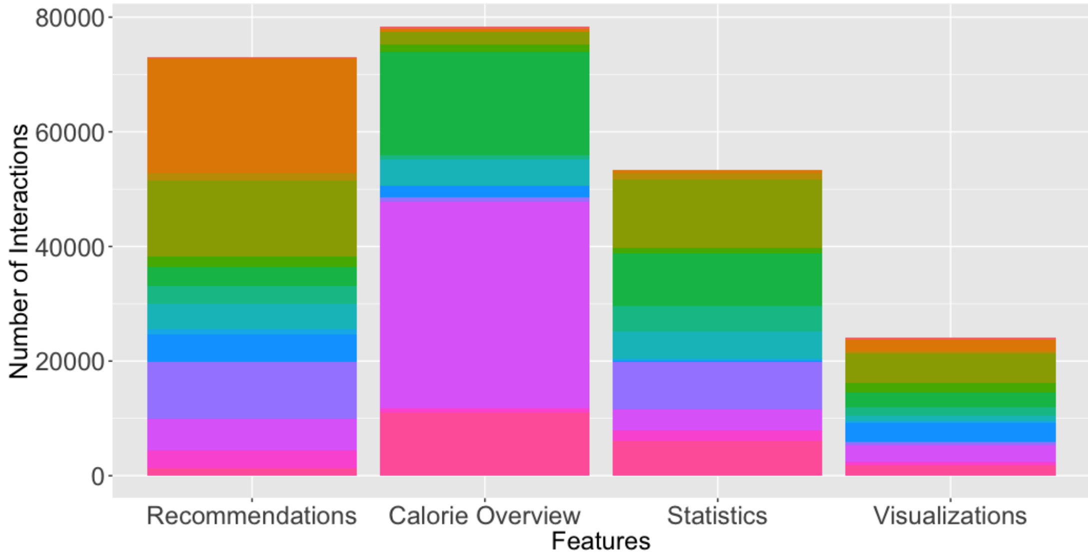


Figure 49: Numer of interactions per screen with users as color-coding.

Figure 50 shows the calories of the user's daily tracking (blue) and the survey-based measurements before and after the study (green). The underestimation of food intake when using daily tracking within the application is around 1000 kCal. The standardized measurement using an FFQ shows a slight decrease in caloric intake after using the applications. The underestimated intake is partially due to missing meals and partially to dropout. The average number of 70 tracked breakfast and dinner items and the average number of 58 tracked lunch items indicates missing data during lunch. At the same time, only nine of the 14 participants used the system for more than 17 days. The health evaluation depends on the number of calories entered and might thus be skewed. This effect is supported by an average number of 13 nutrients that were in the optimal range. Only one participant reached the maximum of 22/26 optimal nutrients after an intervention time of 11 days.

8.5 DISCUSSION OF RESULTS

8.5.1 *Review of Research Questions*

The main feedback of the study is a lack of usability in the given prototype. The challenges for the recommendations screen include adding more recipes and improving the tracking, which in turn influences the personalized advice for future consumption. Concerning the visualizations, the most critical feedback was the message on suboptimal nutrients on the home screen. This message should be switched to positive feedback. Further visual feedback could be added within the intake tracking process to use the large number of interactions spent here. Finally, favorite food items are included to speed up the tracking process. Overall the application received lots of critical feedback on the current state of implementation but also positive feedback on the concept and content.

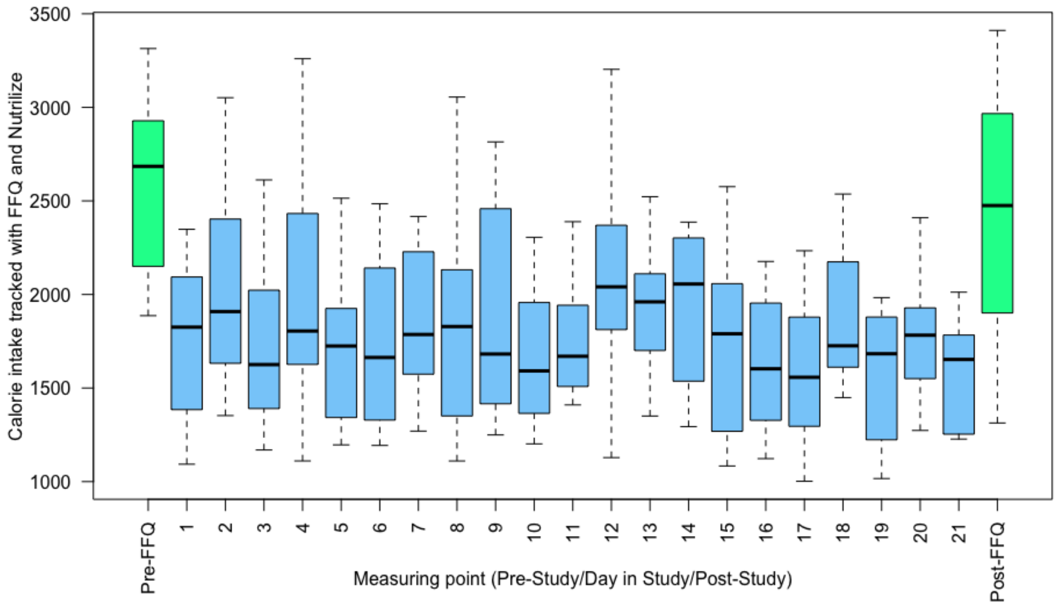


Figure 50: Comparison of reported daily energy intake (kCal) calculated based on the FFQ (green) or on the application based dietary tracking (blue).

8.5.2 *Study Limitations*

The system's prototypical state leads to usability issues that might have impeded the interaction of users in general. Further, due to the low number of participants and the study's short duration, no analysis of improvements in BMI or blood values was conducted. The following relevance cycles will remedy these limitations with larger samples and an improved system variant.

8.5.3 *Future Iterations of Personalized Nutrition Assistance Systems*

The participants' specific comments and the bottlenecks detected in both interactions and nutritional behavior can improve the application for the actual short- and long-term studies. For example, to avoid giving false feedback like "increase fat and sugar intake" due to the underestimation of calories, the algorithm is updated to exclude carbohydrates and total fat intake from the advice vectors. Other desirable improvements for real-life situations were mentioned, but cannot be implemented easily, such as the inclusion of seasonal recommendation, automatic profiling of recipes according to preferred diets (e.g., vegan or raw food) and group recommendations.

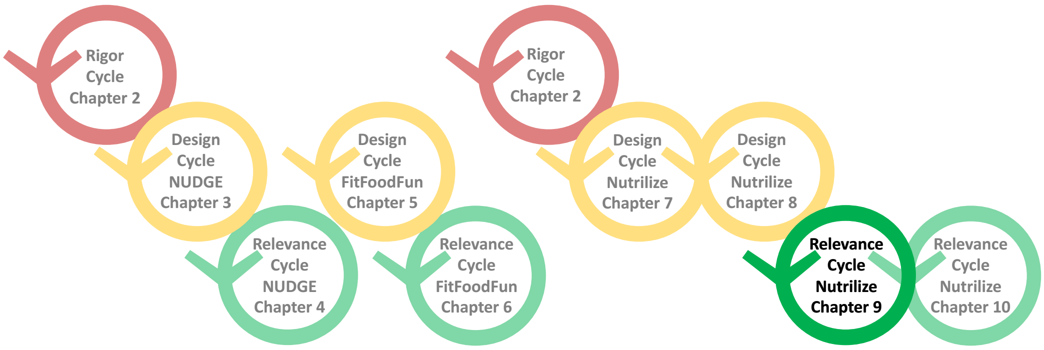
8.6 Conclusion and Next Steps

This pilot study gave valuable insights into the application's usability as a whole and the usage patterns over an extended period. While feedback on as more recipes and increased performance can be applied to the systems, other challenges such as social and contextual personalization remain open. To analyze the effect of the application on the users' nutritional behavior and thus on their physical state, a long term study with the improved prototype is necessary. We elaborate on such a study in chapter 10.

In this chapter, we designed the final algorithmic component underlying the overall *Nutrilize* system. We refined the algorithm with nutrient information from the BLS database, with utility functions from the DRI guidelines, a recipe database based on the KochWiki (Koch-Wiki, 2019), and with a taste preference estimation based on intake history. We further revised the interface layout according to the feedback received in the prior design cycle. During our pilot study of the revised *Nutrilize* system, we derived important insights into users' usage preferences in a real-life context. Some users are focused mostly on weight loss and calorie visualizations, while others utilize the recommender system most extensively. We further observe an indication of differences between the FFQ-based and the diary-based assessment of nutrition. Finally, we see that a great difference in the number of interactions performed between different users, which can be interpreted as the first sign of dropout. In the scope of the final *Nutrilize* system, we address the usability issues detected in this realistic usage scenario. The final system is evaluated in a short-term (chapter 9) and long-term (chapter 10) relevance cycle in the subsequent chapters.

9

TAILORED GOALS FOR NUTRITION ASSISTANCE SYSTEMS



This chapter discusses the results of the first relevance cycle for the *Nutrilize* system. It tests the system's effects using a between- and within-subjects user study on tailored goal setting. This study was conducted in collaboration with the Eindhoven University of Technology and has been published as a full paper at IUI 2019, of which I am the first and main author (Schäfer and Willemsen, 2019). The chapter is entirely taken from this publication. For legibility reasons, any literal citation of my previous publication within this chapter is color-coded in the same gray color as this sentence without giving a citation to (Schäfer and Willemsen, 2019). This chapter aims to assess the effects of using *Nutrilize* in a real-life setting over a short period. Additionally, we investigate tailoring the user's goals to the user's abilities according to a Rasch scale. We evaluated two versions of *Nutrilize*, where the original version targets optimal nutritional behavior and focuses on the six least optimal nutrients (N=51). The adapted version targets only improved nutritional behavior compared to the status quo and thus tailored the advice to the next six achievable nutrients according to a Rasch scale (N=47). We will discuss how the results of the two-week study indicate that the tailored advice leads to higher success for the focused nutrients, and is perceived to be more diverse and personalized, and thus more effective. We will further analyze the internal effects and interdependencies of *Nutrilize* regarding the user's interactions and input.

9.1 MOTIVATION

The psychometric Rasch model has been shown to be an adequate method of tailoring to one's abilities in different areas of application and has helped users with tailored achievable energy-saving or health goals (Starke et al., 2017, Radha et al., 2016). The benefit of such a scale is that it captures all behavioral difficulties to eat healthy in one single scale. For example, constructing a Rasch scale based on the optimal intake of nutrients captures not only those nutrients that are hard to achieve due to taste reasons such as fat and sugar, but also the nutrients that are hard to achieve due to their general availability in commonly consumed food. Additionally, the Rasch scale attributes not only a single dimension difficulty to nutrition, but also connects this scale to single users by measuring their ability on the scale. It represents the probability of a person achieving optimal intake of a certain nutrient as a function of that person's ability and the nutrient's difficulty. For instance, a person whose ability is higher than a nutrient's difficulty level is likely to achieve optimal intake on that nutrient.

Goal setting and adaption of difficulty levels has been discussed in several behavior change theories (Fogg, 2009, Hochbaum et al., 1952, Locke and Latham, 2002). In Fogg's theory (Fogg, 2009), the performance of a task depends on the current motivation and a given action trigger, but also on the ability to perform a given task. The authors thus promote using tasks of highest simplicity according to several criteria, such as time and cost, for increasing the action probability. The Health Believe Model by Hochbaum et al. (Hochbaum et al., 1952) also incorporates self-efficacy as a construct representing action barriers due to lacking ability. Finally, Locke et al. (Locke and Latham, 2002) suggest that the highest effort is reached, when goals are rather difficult and challenging, but just within reach of the person's ability. For implementing any adaption of goals towards the user's perceived difficulty, however, this difficulty of goals first needs to be reliably modeled. One option to model difficulty over a set of items and users is to create a Rasch model.

The Rasch model originates from item response theory (IRT) (Bond and Fox, 2013) and models both persons and measures on a shared one-dimensional scale as shown by Kaiser et al. (Kaiser and Wilson, 2004). The scale represents the probability of performing each behavioral item as a function of a users' ability and the behavioral difficulty (Kaiser et al., 2010). The Rasch scale has previously been used in the context of recommender systems, e.g., for energy-saving measures by Starke et al. (Starke et al., 2017) and for lifestyle changes regarding blood pressure management by Radha et al. (Radha et al., 2016). In both cases, the recommended items themselves are used as a unit of measurement on the Rasch scale. To determine the users' ability level regarding healthy nutrition, nutrients rather than food items can be used as a unit that forms a good level of abstraction. Nutrients not only represent the user's habits in detail but also inherently model the distribution of nutrients in commonly consumed food items.

With this work, we investigate how tailoring goals for nutrition behavior change using a Rasch scale can improve the impact of nutrition assistance systems. More specifically our research questions are:

How will tailored goals influence ...

- **... the interaction with the system?**
- **... the success in behavior change?**
- **... the perception of the system?**

We show how a Rasch scale for tailored goals can be derived from national food consumption data and how a nutrition assistance system can be adapted to include this tailoring. Subsequently, we report our results from a user study in which 98 participants either used the adapted Rasch-based system or the original system over two weeks. We tracked how they used the system, how they changed their nutrition intake, and how they experienced the use of the system. Finally, we discuss how our findings may influence future systems and which drawbacks need to be considered in the design of tailored goals.

9.2 PROPOSED SOLUTION

We examined our research questions using the nutrition assistance system *Nutrilize*. The early design and background of *Nutrilize* is published in (Terzimehić et al., 2016) and a pilot study showing the general usage of *Nutrilize* is reported in (Leipold et al., 2018). For this study, we created two systems variants, which both offer the option to enter one's daily diet and receive feedback on it using visualizations and recipe recommendations. The following sections assess the differences between the two versions of the application: First, the tailoring to participants' ability influences the ranking algorithm for the recipe recommendations. Second, the Rasch model is integrated into the visual feedback on current nutrient levels. Finally, the system offers feedback on the current Rasch ability level in a gamified way. To provide a clear categorization of our system, we shortly answer the most important aspects of the taxonomy for health recommender systems by Hors-Fraile et al. (Hors-Fraile et al., 2018). Our system targets the domain of healthy nutrition for healthy adults by providing tailored recipe recommendations on a mobile Android application. We conducted studies in Germany and the Netherlands measuring users' interaction with the system, their change in nutritional behavior, and their system perception. We provide multiple persuasive system components as categorized in (Terzimehić et al., 2016), but no social components and no medical components.

9.2.1 *General System Description*

The *Nutrilize* nutrition assistance system consists of three main components. First, it offers a dietary diary (figure 51, left) that can be filled with food items from the NEVO database (Westenbrink et al., 2016) or physical activities. The input is given by searching the database and specifying the consumed amount for each item. The second major component is the visual feedback on each nutrient's supply derived from nutritional history. The feedback is either based on the average consumption of the previous three days (figure 53) or based on the full nutritional history (figure 52, right). In addition to the pure data visualization, the feedback includes explanations about the nutrient's benefits, risks, and intake sources (figure 52, left). The third major component of the application is a recipe recommender system. This feature offers ranked lists of recipes for each meal, based on their nutrient content and the users' preferences (figure 51, right).

9.2.2 *Visual Feedback*

The visual feedback is based on the average nutrient supply over the last 3 days. In the original system, this feedback focuses on the six least optimal nutrients by showing them in the home screen (figure 53, left) and reporting them the first position in any list of nutrient feedback. In the adapted Rasch-based system, these six nutrients are determined according to the Rasch scale. They should be the easiest possible

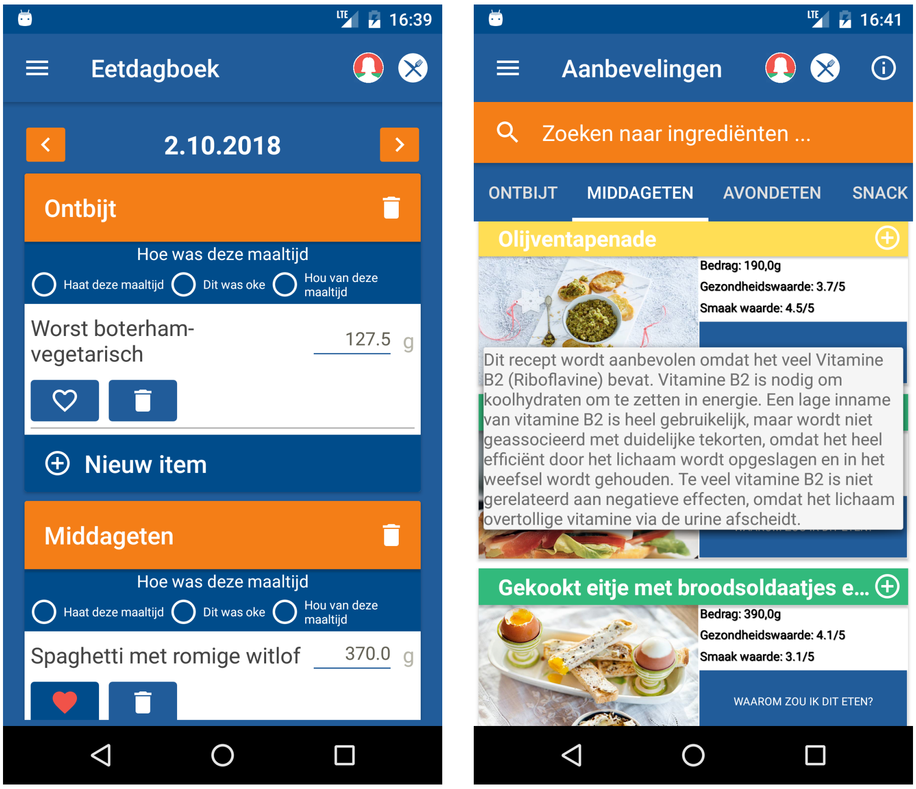


Figure 51: Diary screen (left) and recommendation screen (right). This figure has been taken from (Schäfer and Willemsen, 2019).

items that the user has not already achieved previously, assessed from either the initial survey or the dietary diary. In addition to implicitly adapting the feedback, the application home screen also explicitly refers to the user's current Rasch level in a gamified way. Figure 53 on the right shows this gamification at the top of the home screen saying "You are currently on level 2. Your recommendations focus on these 6 nutrients because they are the easiest for you to improve.". Besides the home screen, the listed nutrient feedback is also arranged by the Rasch scale (figure 54, right) instead of the current criticality (figure 54, left). With these adaptations, we expect the Rasch-based system to provide attainable nutrients levels which should benefit the user experience and the likelihood of improving these nutrients.

9.2.3 *Recommendations*

The recipe recommender algorithm is a hybrid recommender system based on a knowledge-based health recommender algorithm and a taste-based recommender system. The health recommender calculates each recipe's tailored fitness based on the previous nutrient supply of a user and the nutrient content of that recipe. A more detailed description can be found in our previous work (Leipold et al., 2018). The taste recommender calculates the fitness of a recipe based on the systematic distribution of food groups per meal and the recipes distribution of food groups. For example, someone who eats toast for breakfast regularly would have a higher taste rating for

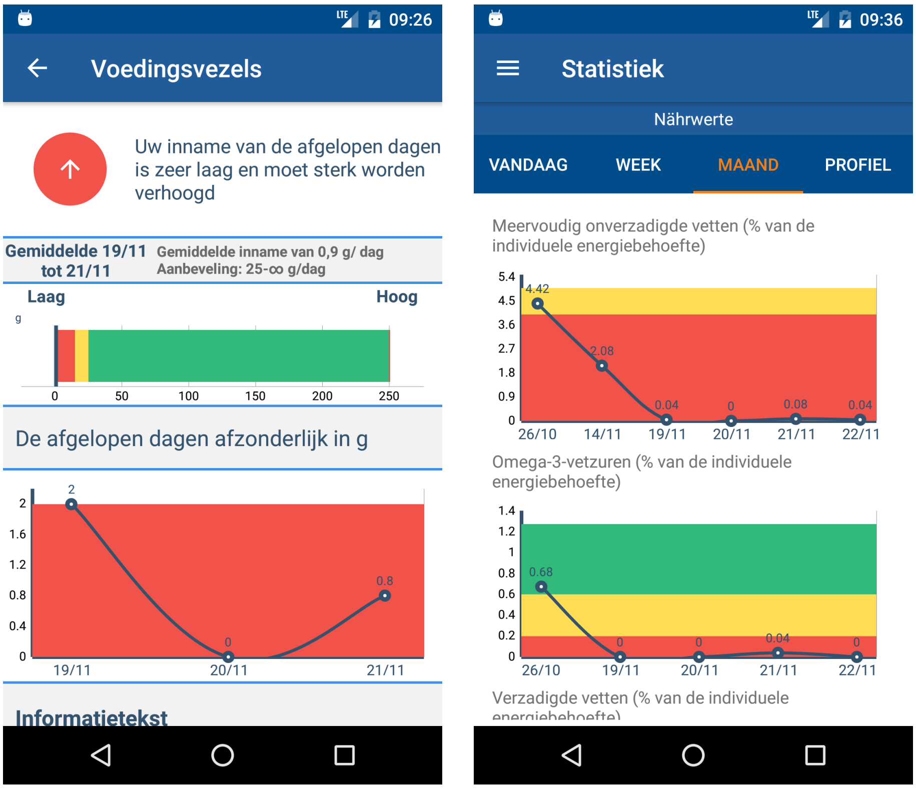


Figure 52: Nutrient details (left) and nutrient statistics (right). This figure has been taken from (Schäfer and Willemsen, 2019).

any breakfast recipe containing a type of bread and even higher for toast. The combined rating of each recipe is calculated with 75% of the health rating and 25% of the taste rating plus a penalty for a rating above 4.5/5 on the previous recommendation. The original system includes all nutrients into the health recommender and gives higher weight to poorly supplied nutrients. The adapted system only includes the six Rasch nutrients into the fitness function. The initial nutritional behavior and dietary preference is determined using a questionnaire before the study.

9.2.4 *Rasch-Scale*

The Rasch model creates a one-dimensional measurement scale, representing the difficulty level (by ordering different items) as well as the ability of people on the same scale as introduced by Bond et al. (Bond and Fox, 2013). In the case of nutrition, there are too many food items to build a useful scale. Instead, we built a Rasch scale on the difficulty of getting an optimal intake of a nutrient. The overall nutrient scale represents different diets and food options. For example, a person with eating disorders might not get enough intake of protein and thus start out very low on the Rasch scale. On the other hand, most people with a regular diet have enough protein intake but might still struggle to receive all the vitamins they require. Such a person might be in the middle of the Rasch scale. Finally, a person with a very healthy diet might still struggle to achieve the correct level of folate, simply because it is not available

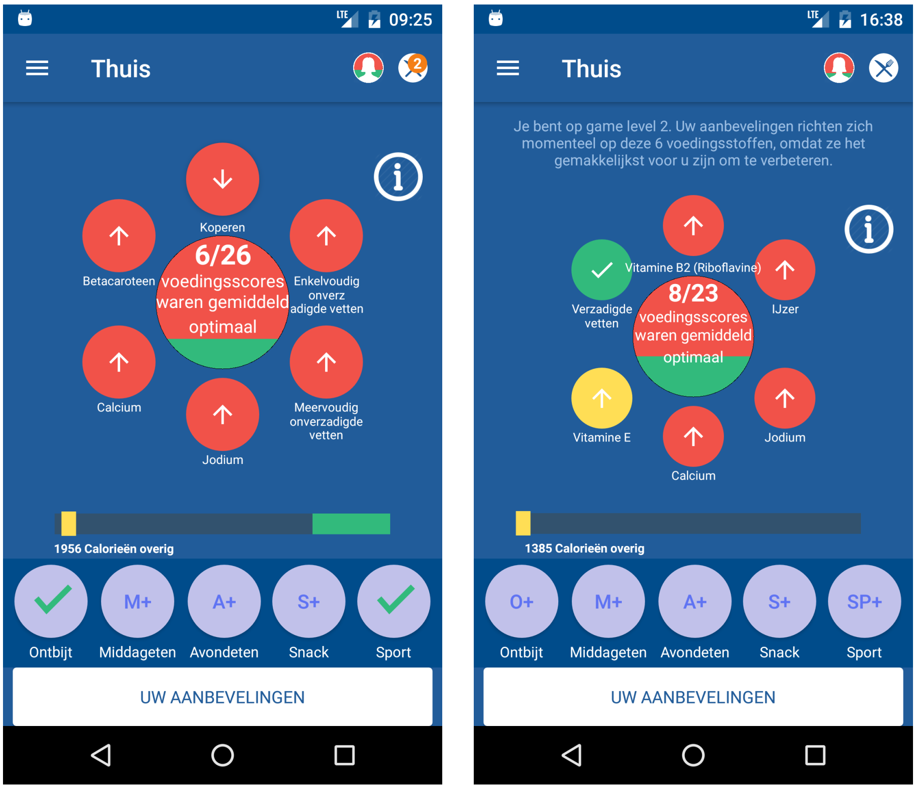


Figure 53: Home screen in original (left) and Rasch (right) system. This figure has been taken from (Schäfer and Willemsen, 2019).

in many common food items. The Rasch scale represents the relation between the difficulty of each nutrient and the ability of a person based on their everyday diet. While the Rasch scale can usually be utilized to predict the probability of a person adopting an item, in case of a nutrient scale, only the probability of a person reaching the optimal intake of that nutrient can be predicted.

The Rasch scale in this project was based on the DNFCS 2007-2010 dataset, which is part of the Dutch National Food Consumption Survey performed by RIVM, Bilthoven (van Rossum et al., 2011). The data contains the self-reported daily intake of 3819 participants on two days leading to 7638 samples. The given dataset already contained the accumulated amount of each nutrient for the self-reported days. The optimal level was determined using the Dietary Reference Intake (DRI) values from the Institute of Medicine (of Medicine (US) Subcommittee on Interpretation and of Dietary Reference Intakes; Institute of Medicine (US) Standing Committee on the Scientific Evaluation of Dietary Reference Intakes, 2000) and the D-A-CH society (für Ernährung Österreichische Gesellschaft für Ernährung Schweizerische Gesellschaft für Ernährungsforschung Schweizerische Vereinigung für Ernährung), 2008). The resulting scales are depicted in table 16 and were calculated using Winsteps 4.0.0 Rasch Analysis software (Winsteps, 2020). We built separate scales based on the two days sampled in the consumption survey to check for inconsistencies. A number of nutrients were not available in the Dutch national food consumption survey and were approximated from other food consumption datasets. We selected their relative position within this final Rasch scale based on the position of their surrounding nutrients in their original scale. Nu-

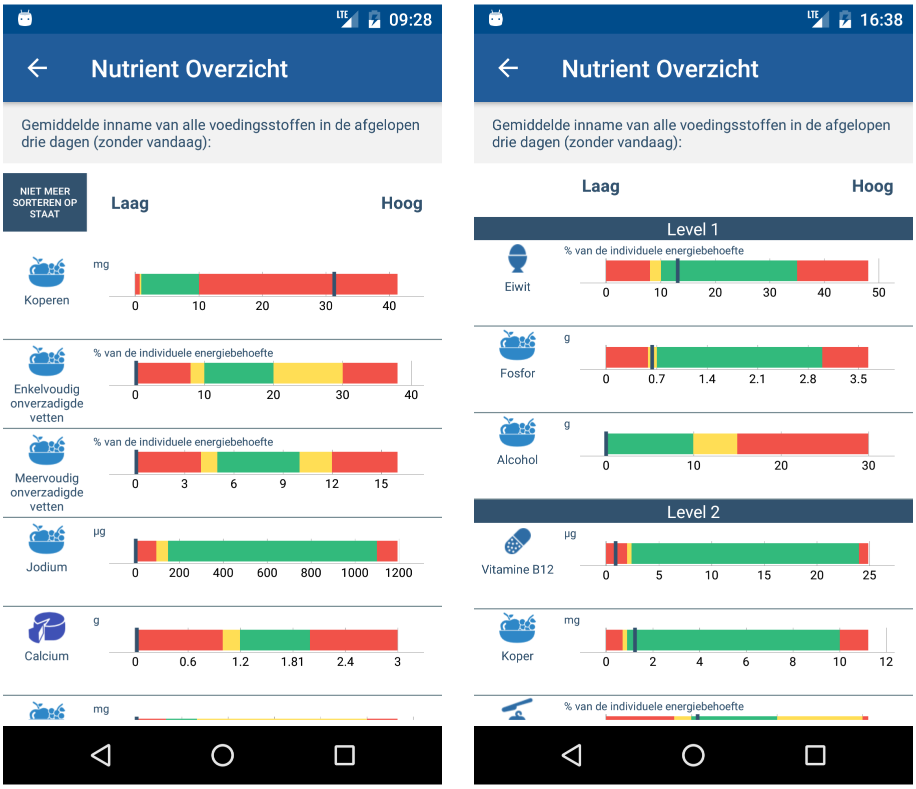


Figure 54: Nutrient list in original (left) and Rasch (right) system. This figure has been taken from (Schäfer and Willemsen, 2019).

trients below -1.5 are in level 1, nutrients below -0.5 in level 2, nutrients below 0.5 are in level 3 nutrients below 1.0 are in level 4, and nutrients above 1.0 on the Rasch scale are in level 5. Using this kind of coarser aggregation, the resulting levels are the same between the two days. The infit and outfit mean-square values are quality measures for the fitting of the Rasch scale. For a reasonable fit, they reside between 0.5 and 1.5. Problematic fits in the Rasch scale are thus Saturated-Fatty-Acids (SFA), Mono-Unsaturated-Fatty-Acids (MUFA), and alcohol. For SFA and MUFA, this might be explained by the dependency of their intake on caloric intake, which is often underestimated in surveys (Gibney et al., 2002). The ability level of a user on this Rasch scale could be determined using the model within the Winsteps software. In our application, we determine the nutrients a person is already consuming optimally and focus on nutrients above those on the calculated scale, without directly calculating the ability level.

9.3 EVALUATION

This study uses a mixed within and between-subject design. One-half of the participants receive the Rasch tailored system while the other half receives the original nutrition assistance system. We expect that the Rasch-based tailoring presents attainable goals that increase motivation, adherence, and, thus, behavior change. At the same time, we monitor the interaction and self-reported diet of all participants over

Table 16: Rasch-scale derived from Dutch food consumption. The table has been adapted from (Schäfer and Willemsen, 2019).

Name	Scale 1	Scale 2	Infit 1	Outfit 1	Infit 2	Outfit 2	Level
Sugar	Approximated from other datasets						5
Fiber	2.2	2.33	0.92	0.72	0.93	0.7	5
Folate	2.23	2.28	0.91	0.68	0.9	0.63	5
SFA	1.32	1.2	1.26	1.87	1.27	1.79	5
Magnesium	0.88	0.92	0.78	0.68	0.79	0.68	4
Vitamin E	0.89	0.88	0.86	0.8	0.9	0.85	4
Omega 3	Approximated from other datasets						4
Calcium	0.62	0.66	0.92	0.86	0.92	0.87	4
Thiamine	0.6	0.64	0.9	0.85	0.89	0.85	4
Vitamin C	0.5	0.49	1.11	1.13	1.12	1.14	3
Iodine	Approximated from other datasets						3
Iron	0.12	0.19	0.94	0.91	0.91	0.88	3
Zinc	-0.09	-0.07	0.82	0.77	0.84	0.8	3
Poly-Unsaturated-Fatty-Acids (PUFA)	-0.37	-0.39	1.13	1.16	1.14	1.19	3
Riboflavin	-0.71	-0.75	0.8	0.73	0.79	0.72	2
Vitamin B6	-0.81	-0.74	0.81	0.73	0.81	0.74	2
MUFA	-0.82	-0.9	1.22	1.38	1.24	1.41	2
Copper	-0.89	-0.87	0.82	0.73	0.81	0.73	2
Vitamin B12	-1.24	-1.25	0.87	0.84	0.87	0.82	2
Alcohol	-1.67	-1.77	1.34	1.97	1.33	1.94	1
Phosphorous	-3.38	-3.38	0.86	0.79	0.85	0.7	1
Protein	Approximated from other datasets						1

a time frame of 12 days. Our expectations are that the persuasive elements change the behavior with time, while on the other hand, both motivation and the number of interactions decrease over time. For the Rasch system we hypothesize that the overall motivation is less likely to decrease and thus the persuasive system elements can affect the behavior for a longer time.

9.3.1 *Study Procedure and Participants*

The study consisted of four distinct steps. The first step all participants had to complete was the screening survey. In this survey, we checked for medical constraints (e.g., allergies, pregnancy, etc.) and technical constraints (e.g., Android phone, internet access, etc.). If the participants qualified for the study and gave us their consent, they received a link to the first survey. In this survey, we collected data on eating habits using a food frequency questionnaire, their activity habits using the Norman questionnaire (Norman et al., 2001) and data on their physiological measures (e.g., height, weight, age, gender, etc.). On the day after the first survey, all participants received the mobile application, an installation manual, and instructions for the first steps via email. On the fourth day of using the application, the participants received another instruction with interesting additional features of the application. After twelve days of using the application, the participants received the final survey. In this survey, we asked for their perception of the recommendations, their experience with the system, and their personality traits. The application was still available to the participants for a few weeks after the final survey.

Table 17: Participant information. This table has been taken from (Schäfer and Willemsen, 2019).

	Screening #	Qualified #	Full Study #	Female %
Pool 1	134	86	68	67.65
Pool 2	152	101	30	80.00
Total	286	187	98	71.43
	Avg. Age	Max. Age	Min. Age	Avg. Physical Activity Level (PAL)
Pool 1	26.66	73.00	18.00	1.58
Pool 2	30.10	42.00	19.00	1.23
Total	27.71	73.00	18.00	1.48
	Avg. BMI	Max. BMI	Min. BMI	Avg. WHR
Pool 1	23.30	37.18	18.21	0.86
Pool 2	24.66	39.89	17.30	0.85
Total	23.72	39.89	17.30	0.86

The participants were recruited from two different research participant databases and received a payment depending on their participation in the study. Of the 286 participants that started the first screening 187 qualified for participation and finished the first survey. The screening excludes any participants that are minors, have food allergies or intolerances, suffer from illnesses, are influenced by diet (e.g., diabetes, liver, kidneys, lungs, heart disease, thyroid disease, anemia), are currently pregnant, are following a strict diet, have no Android device, or have no internet access. Finally, participants are only allowed to proceed with the study once they give their informed consent. Of all the qualified participants, every second participant is put into the "Rasch" group, without any influence of the participant's profile on the group decision. The participants receive access to the application on the day after finishing the screening and the first survey. After 12 days of interaction, the participants receive the final survey. After filling in the final survey, participants were able to receive a reward between 7.50€ and 17.50€ depending on their invested effort (about 2.50€ per 30 min). The final survey was concluded by 98 (70 female) participants. The high female bias has also been experienced in previous studies of our application (Leipold et al., 2018) and is already present before the screening process, hinting at a higher interest of female participants in nutrition. The age of the participants in the final data set ranges from 18 to 73, with an average age of 27.7. The two different participant pools show differences in their characteristics and their behavior. Pool 1 is a participant pool of the Eindhoven University of Technology consisting mostly of (former) students and to a smaller percentage of older people volunteering for studies. Pool 2 is a Dutch open panel used by academics, journalists, sports clubs, but also commercial companies. While the number of participants passing the screening is around 65% for both groups, the second pool has a much higher dropout rate during the application usage (70% compared to 21%). This difference in dropout was mostly due to the fact that different from the first pool, this second pool is used to doing surveys, but no longitudinal studies. Furthermore, our participants from pool 2 have a slightly higher average age as pool 1 but with a narrower age range of 23 instead of 55 years. While the BMI and waist-hip-ratio is comparable between the pools, pool 1 shows a higher physical activity level than pool 2.

9.3.2 *Data Collection*

We had three different types of measurements in this study. First, we measured the participants' behavior within the application using a tracking tool Matomo, formerly named Piwik (Matomo, 2020). This tool provides us with information on each interaction's screen-name and the time of the interactions. Second, we measured the nutrition of participants using both a food frequency questionnaire, and the daily diet entered in the applications food diary. For both nutritional data sources, we collected the amount of each nutrient and the level of optimality of that nutrient according to the guidelines. Additionally, we tracked which of the entered nutrients were focused on the day of tracking. Finally, we measured the users' self-reported perception and experience using a questionnaire on different aspects of the recommendations and the overall system adapted from Knijnenburg et al. (Knijnenburg et al., 2012). We also measured personal characteristics with questionnaires on trust (selected from McKnight et al. (McKnight et al., 2002)), self-control (adapted from Tangney et al. (Tangney et al., 2018)), and Susceptibility to Persuasion Scale (STPS) (by Kaptein et al. (Kaptein et al., 2009)).

9.3.2.1 *Objective Measures*

We derived the users' adherence from tracking their interactions in the application. The tracking tool allowed us to measure the time and number of actions within each application session. The interaction data also indicated a dropout or decrease of interactions for each user. For the purpose of this study, we tracked 13 different screens: food/sports search, food details, diary, home screen, recommendations, nutrient details, nutrient overview, nutrient statistics, calorie overview, preferences, profile, settings.

9.3.2.2 *Self-reported Measures*

We derived insights into the users' diet using two reporting tools. In the beginning, we derived the users' dietary ability from a food frequency questionnaire using 150 common food items. This questionnaire also served as a data source for determining the initial ability of each participant according to the Rasch scale. Afterward, we had the participants track their nutrition within our application for 12 days. Based on the dietary diary, we derived the nutritional intake for each day. We also derived a measure of optimality based on the nutrients reference values. Finally, we tracked which nutrients were shown on the home screen (figure 53) on a given day according to either the current Rasch ability level of a Rasch participant or according to the criticality of the nutrient in the original system.

9.3.2.3 *Subjective Measures*

We surveyed our users on nine subjective constructs. Five of these constructs focused on the perceptions of the recommendations: perceived healthiness (5 items, i.e. "the recommended recipes were relevant for my health"), perceived tastiness (4 items, i.e. "the recommended recipes fitted my taste preferences", perceived personalization (4 items, i.e. "the recommended recipes were well adapted to my eating habits"), perceived diversity (4 items, i.e. "the recommended recipes were very diverse"), and perceived effort of preparing (4 items, i.e. "the recommended recipes were hard to prepare"). Four constructs focused on the interaction with the system: system effort (5 items, i.e., "the *Nutrilize* app worked very easily"), system effectiveness (4 items, i.e., "With the app, I am able to make better dietary decisions"), choice difficulty (4 items, i.e., "Comparing the recommended recipes took a lot of effort") and choice satisfaction (5 items, i.e., "I am happy with the recipes I have chosen"). For all survey items, users indicated on 5-point Likert scales to what extent they agreed with them, which we submitted to Confirmatory Factor Analysis (CFA) using ordinal dependent variables. We excluded preparation difficulty, choice satisfaction, choice difficulty, and system effort as constructs since several items did not load well on the latent construct, and the Average Variance Extracted (AVE) was lower than 0.5, even after removing poorly fitting items. The remaining constructs met the guidelines for convergence validity by Knijnenburg et al. (Knijnenburg and Willemsen, 2015), as at least three items remained, and the average variance explained (AVE) was higher than 0.5. It is surprising that 4 constructs that we measured with scales adapted from existing recommender evaluation research had to be taken out of our CFA. Three of these constructs pertained to the interaction with the recommendations, and as not every user used the recommendation functionality, and the app had many other features beyond the recommendations, the questions might not resonate sufficiently with a user's experience with the entire system.

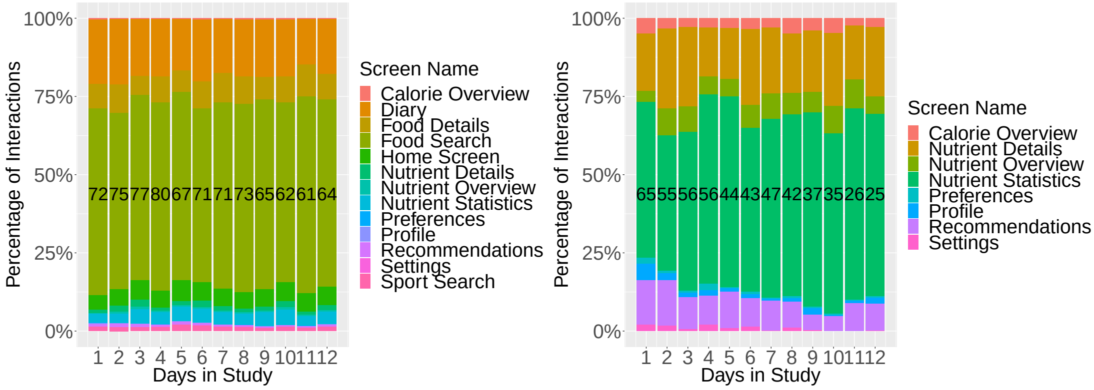
We also asked the participants to fill out constructs to measure their personality characteristics. We asked about their trust using three constructs from McKnight et al. (McKnight et al., 2002): situational normality, the general belief in technology, and trust in technology. We retrieve their self-control using 10 items selected from Tangney et al. (Tangney et al., 2018) translated to Dutch. Furthermore, we retrieved their to persuasion using the 12 items from Kaptein et al. (Kaptein et al., 2009) translated to Dutch. Running CFA on these scales, we noticed that even though these scales are existing scales, our (translated) scales had many items with low factor loadings (R^2 below 0.5). To achieve convergent validity on the self-control scale, we needed to exclude 5 of the 10 items, and the persuasion scale needed to be reduced to only 3 items.

9.3.3 *Results*

9.3.3.1 *Influence on System Interactions*

The first research question is whether the Rasch modification influences the interaction behavior of the users. Figure 55a shows the interactions of both groups on an overall level, while figure 55b shows the same distribution when removing all the interactions related to filling the dietary diary.

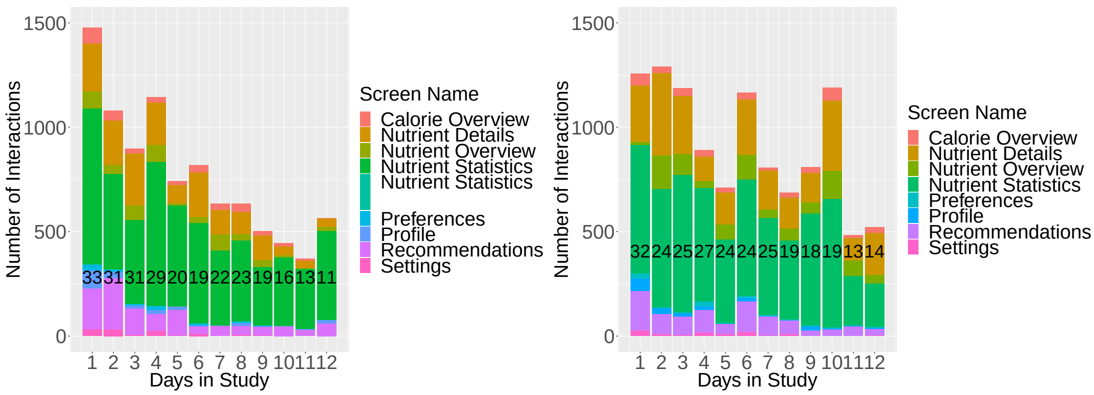
It is clearly visible that the dietary tracking (food search, food details, and diary screen) makes up most of the users' interaction with the system (more than 75%). It is also important to note that there are no great differences between the interaction distributions on the different days in the study (x-axis). Concerning the number of active users, we see a range between 61 and 80 of the 98 participants on the same day.



(a) Daily distribution of interactions over the 13 tracked screens in both system versions. The numbers on each bar indicate individual users on a specific day.

(b) Daily distribution of interactions over the eight important feature screens in both system versions. The numbers on each bar indicate individual users on a specific day.

Figure 55: Relative analysis of system interactions in both systems. This figure has been taken from (Schäfer and Willemsen, 2019).



(a) Interactions with the eight feature screens in the original system. The numbers on each bar indicate individual users on a specific day.

(b) Interactions with the eight feature screens in the Rasch system. The numbers on each bar indicate individual users on a specific day.

Figure 56: Absolute analysis of system interactions in each of the two systems. This figure has been taken from (Schäfer and Willemsen, 2019).

On the feature interaction overview (figure 55b), the statistical visualization of the nutrients over time is clearly the most performed action (figure 52, right), followed by the nutrient details (figure 52, left) and the recommendations (figure 51, right). The interactions with settings, profile, and preference settings decrease in relative importance over the days in the study, which is to be expected due to their functionality. The interactions with the calorie overview (no figure) and the nutrient overview (figure 54) have a similar relative importance during all days in the study, while the recommendation interactions (figure 51, right) slightly decrease. It is also interesting to notice that while the overall usage of the systems stays quite similar, the feature usage shows a strong decrease in users over the course of the study (from 65 to 25).

Figure 56a and figure 56b compare the interactions over the same eight feature screens as in figure 55b. Figure 56a shows the interactions of users with the original system and figure 56b of users with the Rasch system. Both groups show the statistics screen (figure 52, right) as the most used feature. The Rasch group shows a higher number of users on days later in the study (e.g., 14/32 on day 12), while the users of the original system strictly decrease their feature usage over time (e.g., 11/33 on day 12). The Rasch group also shows a higher interest in the nutrient details screen. This may be due to the tailoring of the nutrients shown on the home screen and from which the users may enter the nutrient details screen.

9.3.3.2 *Influence on Nutritional Behavior*

The second research question is whether the Rasch modification influences the nutritional behavior of the users. To build a model about the users' nutritional behavior within the study, we first investigate the interactions of different variables of our dataset (figure 57). The data offers important sanity checks for our measurements. First, we can have a look at the distribution differences between measurements over time (first column). Here we see a slight decrease of the nutrients tracked (similar over study, focus groups and the nutrient success), of the calories entered and of the interactions with the recommendations. The focus of the nutrients (second column) is split between None, Below, Focused, and Above. Focused means that this nutrient is shown to the user on that day in both the home screen and the recommendations. Below means that this nutrient is lower on the Rasch difficulty scale than the highest nutrients that are being focused. Above respectively means that this nutrient is higher on the Rasch difficulty scale than the highest nutrients that are being focused. Finally, the None baseline for the focus variable is measured on days where the application has not determined any focus nutrients, e.g. at the beginning of the study, or after longer periods of missing data. The None group is concentrated on the beginning of the study and has a much lower overall occurrence than the other groups. The focus distribution of the nutrients shows a characteristic difference between the two study groups (third column). Since the original system focuses on the most critical and supposedly thus more difficult nutrients, it has more nutrients below focus than the Rasch system. When looking at the success levels over the different focus groups (fourth column, second row), we see more below focus nutrients are optimal and less of the focused nutrients. When looking at the calories (fifth row), we see a normal distribution over study group and focus level. Finally, the interaction with the recommendations (sixth row) is similarly distributed between focus level, study group and nutrient success.

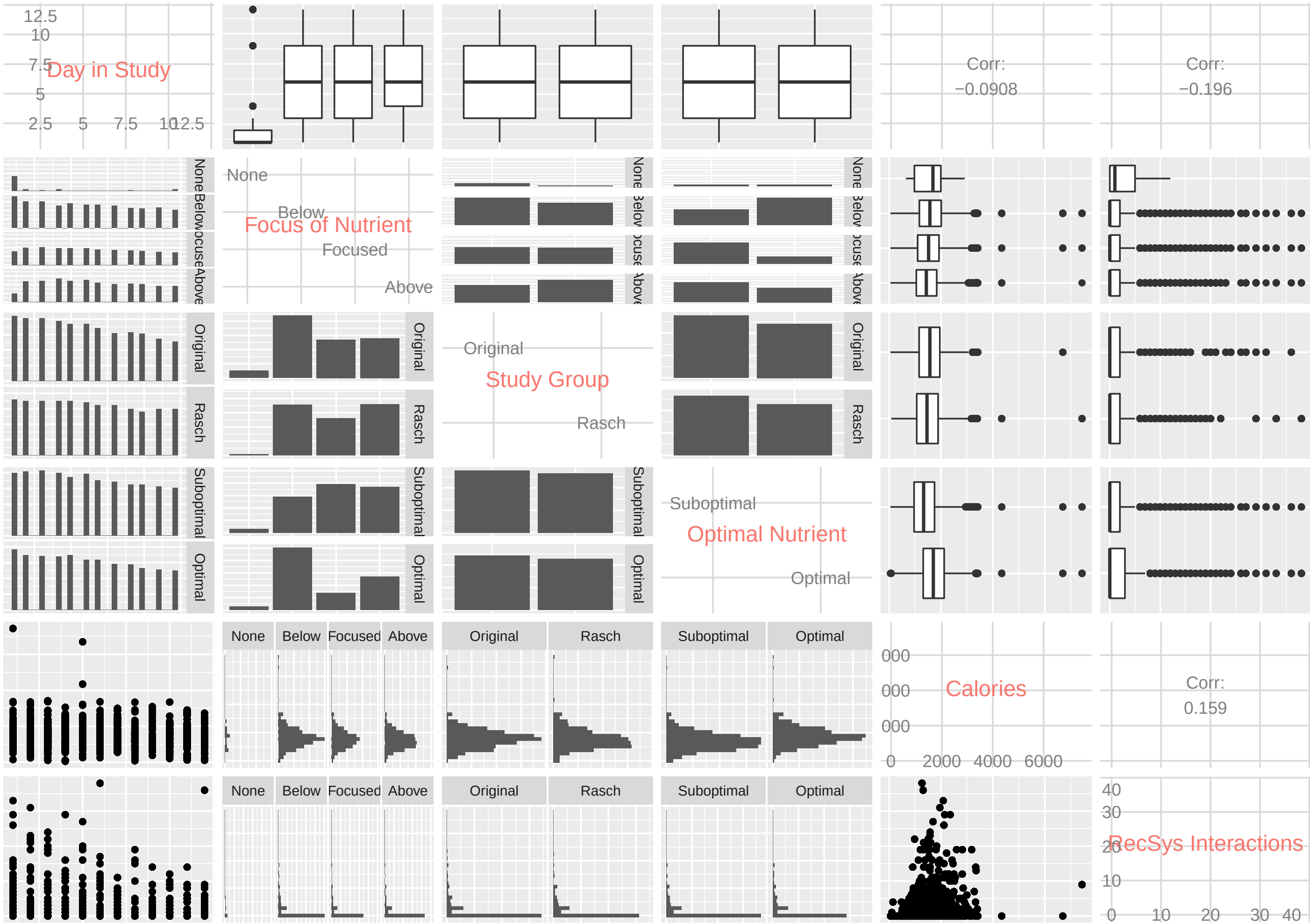


Figure 57: Overview of relevant variables for the behavioral model. This figure has been taken from (Schäfer and Willemsen, 2019).

Table 18: Multilevel logistic regression with one random intercept for users
Minimal Model for Behavior: AIC 23208.6 BIC 23327.3 LogLik -11589.3 deviance 23178.6 df.resid 20239
Extended Model for Behavior: AIC 22002.3 BIC 22168.5 LogLik -10980.1 deviance 21960.3 df.resid 20233
Table has been adapted from (Schäfer and Willemsen, 2019). For each model, the coefficient factor in the linear model, the Standard Error (s.e.), the z-value (coefficient divided by s.e.), and the p-value are given.

Fixed effects:	Minimal Model					Extended Model				
	Estimate	Std	Z	Pr(>|z|)		Estimate	Std	Z	Pr(>|z|)	
(Intercept)	1.92	0.08	23.13	<2e-16	***	1.60	0.18	9.02	<2e-16	***
nutrientLevel2	-2.09	0.07	-27.98	<2e-16	***	-1.85	0.08	-24.14	<2e-16	***
nutrientLevel3	-2.37	0.08	-31.25	<2e-16	***	-2.17	0.08	-27.35	<2e-16	***
nutrientLevel4	-3.00	0.08	-38.51	<2e-16	***	-2.64	0.09	-30.73	<2e-16	***
nutrientLevel5	-2.10	0.08	-27.66	<2e-16	***	-1.75	0.09	-19.87	<2e-16	***
calories	1.23	0.08	15.85	<2e-16	***	1.23	0.08	15.74	<2e-16	***
recommendations	0.07	0.02	3.87	0.000	***	0.08	0.02	4.21	0.000	***
rasch	-0.06	0.10	-0.60	0.546		-0.36	0.33	-1.09	0.274	
normalDate	0.00	0.01	0.51	0.609		0.001	0.01	1.63	0.103	
todayBelowFocus						0.47	0.16	2.90	0.004	**
todayInFocus						-0.90	0.16	-5.51	0.000	***
todayAboveFocus						0.24	0.16	1.46	0.145	
nutrientLevel2:calories	-0.70	0.08	-8.32	<2e-16	***	-0.66	0.09	-7.75	0.000	***
nutrientLevel3:calories	-0.29	0.09	-3.30	0.001	***	-0.26	0.09	-2.95	0.003	**
nutrientLevel4:calories	-0.20	0.09	-2.28	0.023	*	-0.16	0.09	-1.79	0.073	.
nutrientLevel5:calories	-1.40	0.08	-16.73	<2e-16	***	-1.35	0.08	-16.00	<2e-16	***
rasch:normalDate	0.02	0.01	1.69	0.092	.	0.03	0.01	2.71	0.007	**
todayBelowFocus:rasch						0.45	0.32	1.40	0.163	
todayInFocus:rasch						0.86	0.33	2.63	0.009	**
todayAboveFocus:rasch						-0.32	0.32	-0.98	0.329	

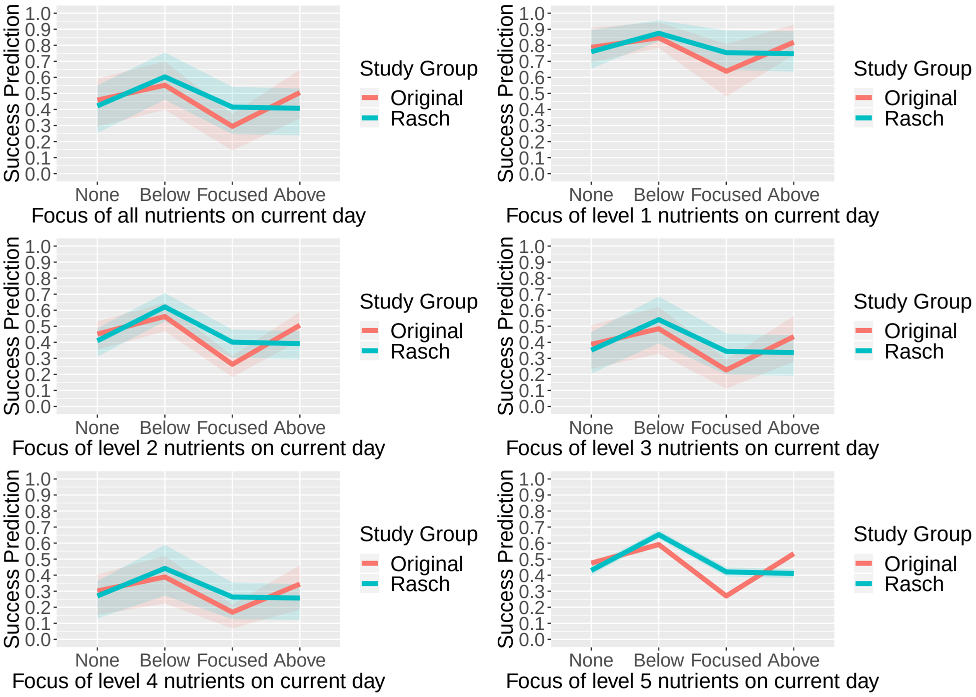


Figure 58: Visualization of the model's prediction for each "today" focus level (None, Below, Focused, Above). The upper left graph shows the prediction across all Rasch-levels, while the subsequent graphs show it for each level (1-5). This figure has been taken from (Schäfer and Willemsen, 2019).

We built two multilevel logistic regression models for analyzing the differences in successful behavior, represented by the optimal consumption of a nutrient on a certain day, between our study groups (table 18). I.e., the model estimates for each nutrient whether the level was achieved or not (taking into account the repeated observations and controlling for participant differences using a random intercept). Our first model measures the effect of "rasch", which is a zero-centered representation of the study group while controlling for many other factors. We included "calories" since our previous research (Leipold et al., 2018) suggests that calories are often underestimated in mobile diet tracking. We included the "nutrientLevel" of the item in 5 categories according to the Rasch scale (see also table 16) to cover differences in the difficulty level of the nutrients. When selecting possible intervention factors, we included the number of recommendation interactions of a certain day as "recommendations", since we see a difference in the interaction data for recommendations. We included the "normalDate" which is the date normalized to day 1-12 in the study since not all participants started simultaneously, to see how the people improve their nutrition over time.

On a first look, there is no significant effect between the Rasch and the original system (coef. -0.06, $p > 0.1$). We can, however, confirm some of the effects we added to compensate for external influence factors. The success of an item is significantly ($p<0.001$) lower with an increasing Rasch difficulty level. For example, "nutrientLevel2" has a negative coefficient of -2.09 and "nutrientLevel3" already of -2.37, showing that nutrients at the level are less likely to be successful. One exception is the fifth level (coef. -2.10). Here, however, we also see a strong interaction effect of the entered calories and that fifth level (coef. -1.40 p<0.001). We also see such an interaction effect between calories and the other nutrient levels, but with a lower effect size (-0.7 (p<0.001),-0.29(p<0.001),-0.2(p<0.05) respectively). This interaction might result from nutrients such as sugar, saturated fatty acids, and mono-unsaturated fatty acids whose intake is highly correlated with the amount of total energy intake. We see no positive influence of the normalDate or the interaction of that factor with the "rasch" factor. Finally, we see a positive effect of the interaction with the recommendations of the system (coef. 0.07, p<0.001).

One reason why our first model might not show an effect of Rasch is that it affects only the 6 nutrients that are in focus and not the other nutrients. Our second model takes this into account by adding the focus level of each nutrient on the current day ("today"). A "todayInFocus" nutrient is thus one of the 6 nutrients shown on the home screen and used in the recommendations on the day the nutrient's success was measured. The "noneFocus" level serves as a baseline for this factor in the model. Looking at this extended model, we confirm that none of the effects in the minimal model - the "recommendations", the "nutrientLevel", the "calories", and their interactions - have changed much (table 18). The overall effect of the "rasch" intervention has no significant effect concerning the "noneFocus" baseline. The other effects of "rasch" are represented by the interactions between "rasch" and the "focus" groups, which we discuss below. The changes over time now have an interaction effect with "rasch" (coef. 0.03 p<0.01), suggesting that success rates increase over time for the Rasch system. When comparing the minimal with the extended model, the likelihood ratio test results in a significantly better fit when considering the focus groups with $\chi^2(6) = 1218.3, p < .0001$. So, we further investigate the effects of these focus groups.

Since the focus group effects are dummy-coded in our model, it is difficult to understand their overall effects and how they interact with the "rasch" factor. To better interpret these effects, figure 58 shows the predictions of the model on each focus level, for both study groups. The separate graphs distinguish between different levels of the Rasch scale and show that although the overall success probability might be lower for higher/difficult Rasch levels, all levels show the same behavior pattern between the focus levels. Furthermore, it is important to note that the baseline "noneFocus" is very similar between the groups, giving another sanity check to the data. The patterns visible in all six graphs show that, for both study groups, the nutrients that are below the given goal set of focused nutrients have the highest predicted success rate (todayBelowFocus: coef. 0.47 p<0.01). Compared to this, the focused nutrients have the lowest success prediction, since they are specifically selected in both systems to represent nutrients that are not achieved yet (todayinFocus: coef. -0.90 p<0.001). However, the Rasch group performs better on the focused/tailored nutrients (todayInFocus:rasch: coef. 0.86 p<0.01) across all levels of difficulty, as is clear from the graphs. Finally, in the "rasch" group, the "belowFocus" nutrients are performed slightly better, and the "aboveFocus" slightly worse. Both effects are not significant.

9.3.3.3 *Influence on Subjective Perceptions and Experiences*

The third research question is whether the Rasch modification influences the perception of the system by the users. In our CFA analysis, we excluded 4 constructs, leaving 5 constructs to help us understand the user perceptions (Perceived healthiness, tastiness, personalization, and diversity) and subjective experience (perceived effectiveness) and whether the Rasch-based system differed from the original system. We conjecture that these Rasch-based nutrients might be perceived as less healthy, but perhaps tastier and more personalized (as they are the easier to attain nutrients). Rasch-based nutrients might also make the recipes more diverse, as they won't be showing the most difficult nutrients all the time. We expect the Rasch-based system to be perceived more effective in helping to achieve the right levels of the nutrients than the original system and that the four perceptual constructs might explain this increased effectiveness partly i.e., the perceptions mediate any potential effect of the Rasch-based adaptation on effectiveness.

The extent to which Rasch might affect the perceptions might be moderated by one's current ability, as the sort of nutrients recommended, and the extent to which they differ from what the original system offers, might be quite different between people with high and low ability. In our modeling, we investigate this potential moderation by including the interaction between Rasch and ability on user perceptions and experience.

We explored all potential relations of the Rasch manipulation on the four perception constructs and on the user experience using SEM. Initial saturated models, including all potential relations, revealed high correlations and cross-loadings between healthiness, tastiness, and personalization. As the effect of personalization on effectiveness was the clearest and most stable path in several models, we decided to drop healthiness and tastiness and keep the personalization. We found that diversity was related to both personalization and effectiveness. Diversity was also the only construct affected by the manipulation which happened to be moderated by ability after further inspection, which we discuss further below. Our final SEM model showed that there was a clear path from Rasch (moderated by ability) on diversity, which subsequently affected effectiveness both directly (negatively) as well as indirectly (positively) via perceived personalization. These two effects clearly show the opposing forces that diversity brings: to some extent, diversity is detrimental to effectiveness, but as it brings a more personalized experience, the net effect is that Rasch improves diversity, which increases effectiveness. Indeed, the total indirect effect of the Rasch by ability interaction via diversity and personality on system effectiveness was positive and marginally significant (0.266, s.e.=0.144, p=.065).

We also tested whether any of the constructs in our SEM model were influenced by the personal characteristics. Persuasion susceptibility or trust did not affect any of our constructs, but we did find that the level of self-control influenced participants' ability to perceived diversity in the recommendations. Finally, we linked the constructs to behavioral measures of engagement we captured in the clickstreams and found that perceived effectiveness is positively correlated to the number of events per visit. The final model (figure 59) had an adequate fit ($\chi^2(128) = 173.929, p < .01, CFI = .97, TLI = .96, RMSEA = .061, 90\%\ CI : [0.036, 0.083]$)

To better understand the effect of "rasch" on diversity and how it was moderated by ability, we computed the marginal effects of these factors on diversity in Figure 60. We observe that in the original system, perceived diversity goes down with ability, whereas in the Rasch-based system, users of all ability levels perceive the same (higher) diversity level. In other words, Rasch tailoring overcomes that recommendations become too similar (less diverse) for higher ability people which subsequently positively influences perceived personalization and effectiveness.

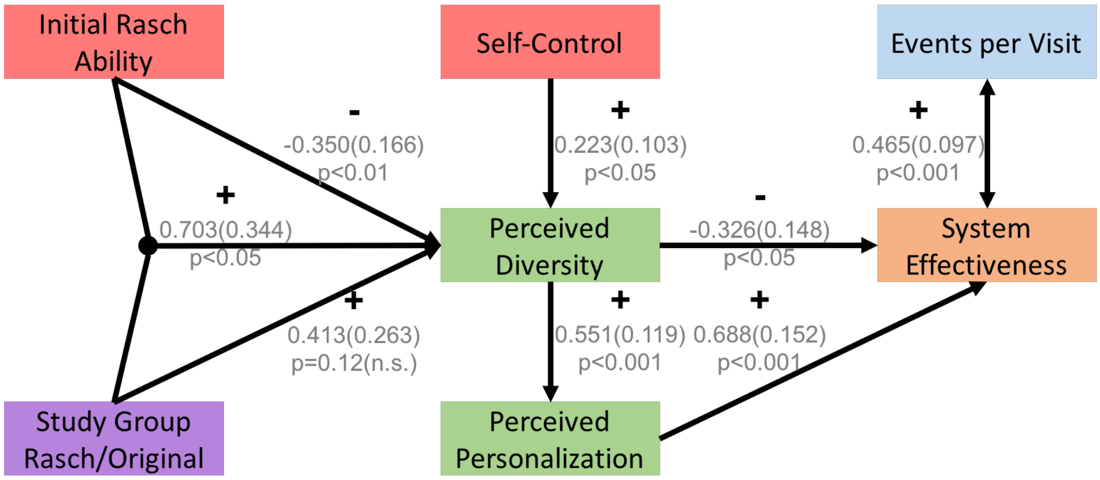


Figure 59: Structural Equation Modelling (SEM). This figure has been taken from (Schäfer and Willemsen, 2019).

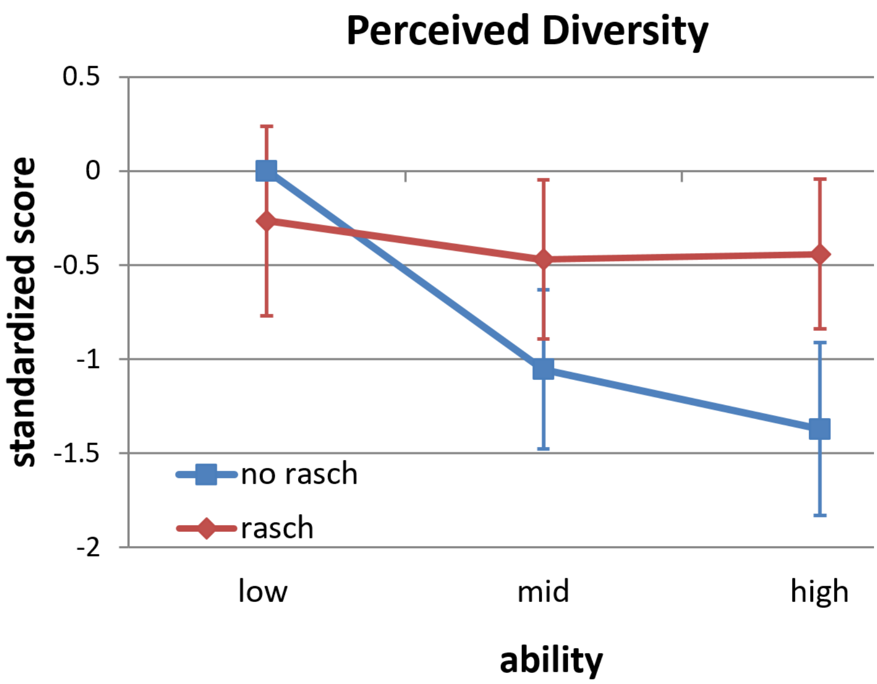


Figure 60: Marginal effects of Rasch and ability on diversity. This figure has been taken from (Schäfer and Willemsen, 2019).

9.4 DISCUSSION OF RESULTS

Several behavioral theories suggest an impact of goal setting on motivation (Fogg, 2009, Hochbaum et al., 1952, Locke and Latham, 2002). In our study, we investigate how tailoring goals to an area of easily reachable goals influences the behavior compared to setting very difficult/high goals. While such goal setting has already been tested, e.g., in the energy domain (Starke et al., 2017), our study offers a broader perspective on the longitudinal effect along two weeks of intervention. Furthermore, the system not only investigates the user's intent to fulfill a goal but measures the actual actions performed.

9.4.1 *Review of Research Questions*

Based on our study, we can not confirm any strong impact of the tailored advice on the interactions within the system, though we do observe somewhat more activity in the Rasch group towards the end of the study. This lack of effect might be caused by the specific setup of the application and the subtle integration of the tailoring in the systems interface. At the same time this shows that any effect of Rasch on nutritional behavior is not mediated by increased activity.

Concerning our second research question, we show that a tailored set of reachable goals leads to a better success rate on the targeted goals compared to goals of the highest difficulty. We also see slight improvements over the course of two weeks among the Rasch-based group. To what extent this result transfer to longer-term effects is still unclear. Within a timeframe of two weeks we cannot determine whether the positive effect of tailoring the advice to reachable goals hold over the whole Rasch scale or that the advice just helps people to attain the less difficult items, due to the focus on the attainable goals.

For our third research question, we discovered that tailoring the recommendations to the person's ability keeps the perceived diversity of the recommendations high, whereas, for the normal system, the diversity drops with increased ability. This diversity is an important factor for the perceived personalization and the overall perceived system effectiveness of the application.

Lack of diversity is a factor that has also been criticized in our previous studies (Leipold et al., 2018) since it is inherently caused by optimizing for the same preferential habits and similar nutritional deficiencies over time. Thus, having higher perceived diversity by tailoring the recommendations to a user's ability is a very useful side effect.

9.4.2 *Study Limitations*

The nutrition assistance system we used to evaluate our hypothesis has clear constraints on how tailored advice is visible within the system. Furthermore, tracking nutrition via a mobile application introduces errors to the resulting dataset. We try to abstract the result measurements by focusing on the nutritional behavior and user perception, more than the specific actions in the application. We furthermore include moderating variables into our model that accounts for the errors in underestimation and the difference in difficulty introduced by the algorithm. From a recommender systems perspective, our study is quite unique as it measures people's interaction over a period of two weeks, showing actual improvement of nutritional intake. However, from a Nutrition Science perspective, this period might be too short. Finally, the study is limited to a Dutch population from only two different participant panels leading to biases, especially in the nutritional behavior data derived. Future research could consolidate the results found by comparing other nutrition assistance systems or even other domains that integrate Rasch-based tailored advice.

9.4.3 *Tailored Goals in Future Systems*

This study contributes to tailored goal setting in behavior change systems, not only be giving further proof of the effectiveness of such a feature but also by elaborating the way the results are influenced. Tailoring recommended action goals to the user's ability is a generic mechanism and could be transferred to a variety of behavior change domains given that a Rasch scale can be derived from previous datasets. For example, fitness applications are very dependent on the ability level of the user and are typically used over a longer-term with adapting recommendations. However, since the study only lasted two weeks, long term effects might differ once the users passed all the low difficulty items.

In addition, our study shows the importance of personalization in general on both the actual success rate of improving nutrient intake as well as the perceived system effectiveness of our nutrition assistance systems.

In the past personalized nutrition advice has been researched in terms of the effectiveness of the suggested intervention by Zeevi et al. (Zeevi et al., 2015), but only rarely in terms of the perceived system effectiveness as done by Celis-Morales et al. (Celis-Morales et al., 2016). The research we report serves as a further step for future work in that direction.

Despite the benefits of tailoring advice towards a persons' ability, we also should consider the ethical implications of withholding information on the nutrients outside the user's reach. For example, users might be less empowered to reach their own conclusions about their diet based on the tailored advice given to them. Even more so, if they stop using the application early on, they might have incorporated a wrong decision system into their daily habits. Although such effects cannot be seen within the scope of this study, future scientific or commercial systems incorporating such tailoring should be aware of the risk and integrate appropriate safeguards.

9.5 CONCLUSION AND NEXT STEPS

This paper presents a study that explores and test the effects of tailored goal setting in nutrition assistance systems concerning i) the system interaction, ii) the nutritional behavior change, and iii) the perception of the system.

For that purpose, we report a study over two weeks with two different intervention groups (N=51 and N=47) with a nutrition assistance system that was designed to offer detailed dietary tracking, personalized visual feedback, and tailored recipe recommendations. For this study one system variant was additionally equipped with a tailored goal setting according to our derived Rasch scale for nutrients which is visible to the user within the nutrient visualizations, focusing on reachable nutrients only, and the recommendations, presenting recipes that optimize only reachable nutrients.

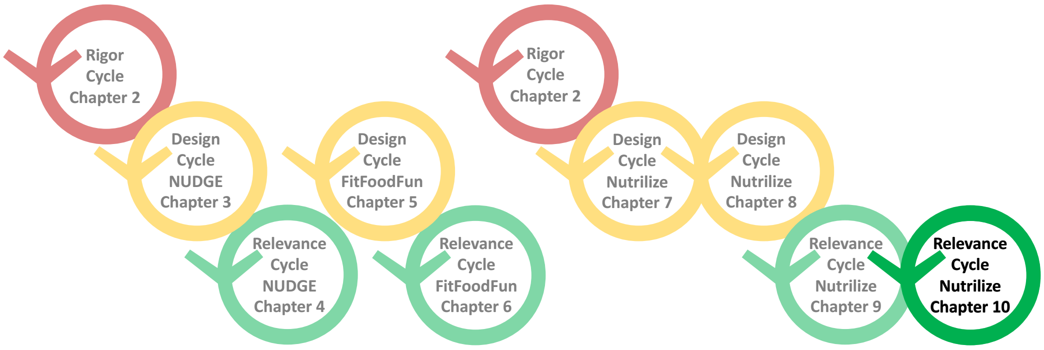
Our results suggest that the interactions with the system shows only small differences between the original and the Rasch-based variant. For the nutritional behavior, we show a higher overall success rate for the tailored advice, especially on changing the behavior of the goals that were presented in focus. For the user perception, we see an impact of the tailored goal setting on the perceived diversity of the recommendations which in turn leads to a higher perceived personalization and system effectiveness.

In summary, our contribution shows positive effects of tailored goal setting on both nutrition behavior change and the perceived effectiveness of the nutrition assistance system. Findings of this approach could in the future be transferred to multiple domains of behavior change, such as getting more fit through physical activities, improving energy efficiency by the implementation of saving measures, or reducing the stress level in workplace environments.

In this thesis's scope, the first relevance cycle cannot yet confirm an effect on nutritional ability by the *Nutrilize* system. However, we observe several internal effects that result from the users' real-life interactions with the system. We observe a drop in the number of interactions over time, especially regarding the recipe recommendations. We confirm the variation in the difficulty of different nutrients that had been derived as a Rasch scale. We further note a strong influence of the amount of tracked calories on the optimality of nutrient intake. This correlation influences the overall system of *Nutrilize* since the visual feedback and recommendations rely on the tracked optimality of nutrient intake. On the other hand, we see a positive impact of using the recommendation feature on nutrient intake optimality. In the following relevance cycle, a longer duration is targeted to provide more insights into the effect of *Nutrilize* on the nutrient intake optimality.

10

STUDY ON LONG-TERM EFFECTS OF NUTRITION ASSISTANCE SYSTEMS



This chapter discusses the results of a user study on the long term effect of a nutrition assistance system on the user's nutrition, the interaction with the application, and the integration of the application in the users' everyday lives. The study uses mixed quantitative and qualitative data analyses to give more in-depth insights into the correlations shown in chapter 9. These results have not been published yet, but a paper comprising this chapter's contents is in preparation. As shown in the related work and market review (chapter 2), nutrition applications have become widely researched and used in the past years. This chapter combines the research on long-term effects typical for nutrition interventions, with the personalized and in-time nutrition feedback of the *Nutrilize* application. In our previous chapters on user studies of nutrition assistance systems (chapter 9, chapter 8), we discuss how our nutrition assistance system *Nutrilize* is used on a short-term basis and how it affects the user's nutritional behavior and the interactions with the system itself. This relevance cycle discusses a long-term user study with 34 users in different study modes (control group 11, intervention group 11, qualitative group 12, group with both control phase and qualitative phase 5). Finally, we discuss how our findings may be limited by the given study setting and how the results could influence the design or extension of other nutrition assistance systems.

10.1 MOTIVATION

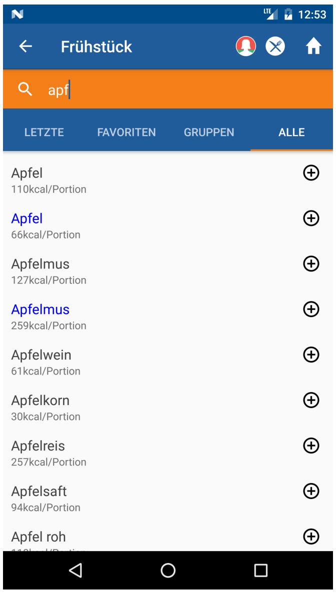
The market for mobile technology supporting a healthier lifestyle has grown strongly in the past years (Swinburn et al., 2011). However, many of these systems suffer from dropout after a short time of usage. After showing the short-term effect of *Nutrilize* in chapter 9, we also need to assess the impact of our system in the long term. Design elements that have been shown to improve engagement, such as mobile application designs (Bert et al., 2014) persuasive components (Orji and Moffatt, 2016) and personalization (Celis-Morales et al., 2016), are already integrated into *Nutrilize*. However, it is still unclear which of these elements impact the user's perception of the system and the behavior changes. Especially for the personalized recommender system, there are mostly short-term and almost no long-term studies to derive expectations from (Knijnenburg et al., 2012). On the other hand, in traditional nutrition interventions, short-term on evaluations are rare, since behavior often changes only affect the physique after a longer time. To address all of these issues, we conducted a long-term study with the *Nutrilize* system. Participants would fill in standardized pre- and post-test questionnaires at fixed intervals. In between these assessments, they were free to use the *Nutrilize* system as they preferred. In comparison with traditional nutrition interventions, we assess the improvement in eating behavior and physique. To discriminate between the effects of different features, we track all user interactions within the system and measure their optimal nutrient intake impact. Finally, to gain insights into the user's thoughts, experiences, and reasonings, we conduct in-depth interviews at different study time points.

10.2 PROPOSED SOLUTION

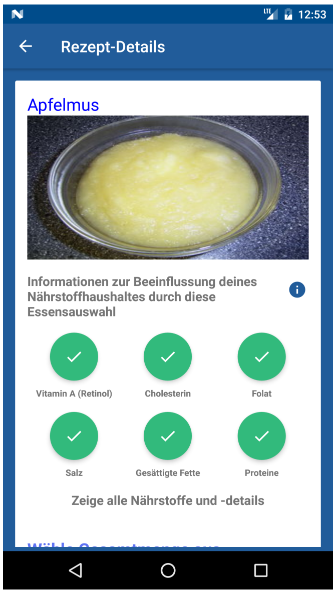
We examined our research questions using the nutrition assistance system *Nutrilize*. The early design and background of *Nutrilize* is discussed in chapter 7 and a pilot study showing the general usage of *Nutrilize* is discussed in chapter 8. Chapter 9 investigates research questions revolving around the most recent version of the system, but with a Rasch-based tailoring and a Dutch target group. This section summarizes all the features and their functionality in the final system version. First, we discuss features necessary for tracking the participants' daily dietary intake, namely the food-search, the food-details, the sports-search, and the diary. Second, we elaborate on the recommendations feature. Third, we discuss all visual feedback screens, namely the statistics screen, the nutrition status screen, the home screen, and the calorie overview. Finally, we review the administrative features such as the preference screen, the profile screen, the login screen, and the settings screen.

10.2.1 *Tracking Features*

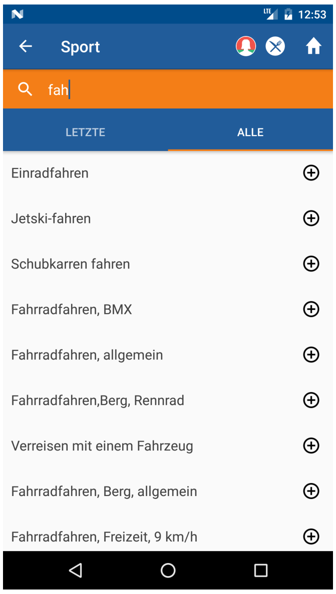
The tracking of each user's diet is done using a search interface (figure 61a). The user can either conduct a free text search, select the food item from a tree structure, or select one of his/her recent or favorite items. When choosing a food item, the user can either directly add the default amount by clicking on the + button, or first click on the food item to receive more detailed information on the food's nutrients and choose a custom portion size to add to the diary (figure 61b). The same mechanism is given for entering physical activity (figure 61c). Instead of portion sizes, the users should choose the amount of time they conducted the physical activity. Finally, the users can review and update all their entered food items in the diary. They can also enter food for past days or delete wrong entries (figure 61d). Providing an extensive tracking tool is essential for computing personalized feedback features on dietary behavior. Additionally, it is important to make the tracking as easy as possible since it produces the highest effort for users and often leads to dropout in dietary applications.



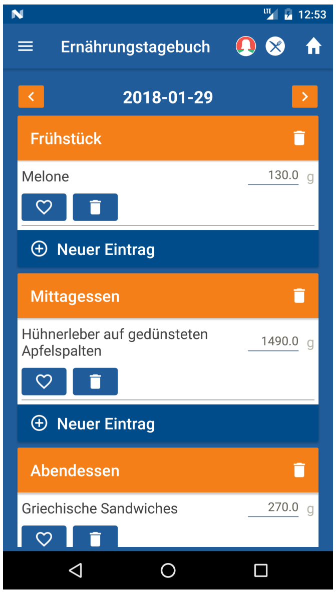
(a) The food search lets the user crawl the BLS database for food items and add them to the diary.



(b) The food details screen shows portions sizes, food images, and small icons to hint at the positive or negative effect of eating this item.



(c) The sports search lets the user crawl a list of activities and add them to the diary for added calories.



(d) The diary screen shows an overview of food and sports items tracked and lets the user correct his history.

Figure 61: Different screens used for tracking dietary intake in the *Nutrilize* prototype.

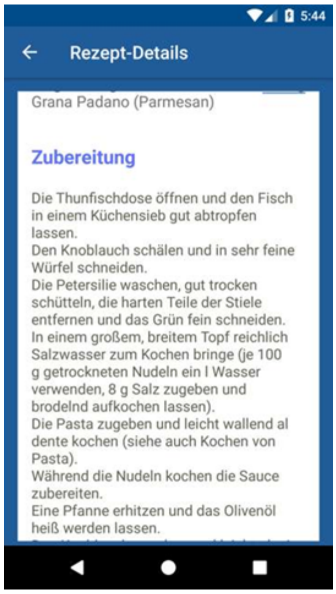
10.2.2 *Recommendation Features*

The recommendation feature shows a list of recommended recipes split by meal type to the user (figure 62a). The recipes' ranking is based on a mix of 75% of the health rating and 25% of the user's taste rating. Further details are discussed in section 8.2. The

(a) The recipe overview shows recommended recipes for each meal and indicates their healthiness with a color-coding.

(b) The recipe explanation gives nutrient-based reasons for recommending this recipe and the benefits of the mentioned nutrients.

(c) The recipe ingredients are shown as part of the recipe details screen.



(d) Recipe instructions are shown as part of the recipe details screen.

Figure 62: Different screens used for recommending recipes in the *Nutrilize* prototype.

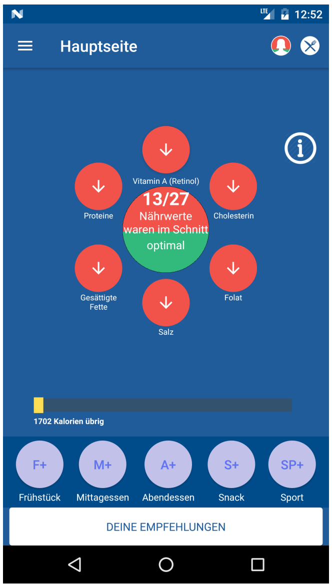
taste rating is based on the relative amount of food types in the user's dietary history. The user can scroll through the recommendations and get an explanation of why the recipe was recommended when clicking the respective button (figure 62b). The user can furthermore open the recipe and see all related information on ingredients (figure 62c), instructions (figure 62d), and the nutritional content of the recipe such as in the food details screen (figure 61b). The recipe recommender targets two different aspects of behavior change. First, it provides users with complete instructions on what to eat best and how to prepare it, so there is no need for multifaceted choices. Second, it empowers the user by reflecting the ratings based on their previous consumption and giving personalized explanations on the system's decisions.

10.2.3 *Visualization Features*

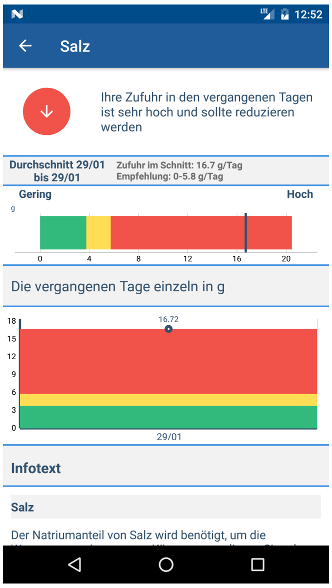
The users can receive visual feedback on their nutritional behavior in different ways. The most prominent feature is the home screen that is shown every time the user opens the application (figure 63a). Here the users see the six most critical nutrients and how they should improve them. The home screen also shows a message about how many nutrients are currently optimal. The users have two options for getting more detailed insights. One option is clicking on one nutrient to get to the nutrient-details screen (figure 63b). Here they can see their progress over the last three days and receive information on the nutrient itself, such as the food it is prominent in and its effects on the body. Additionally, the users can click on the home screen's middle bubble to get an overview of all nutrients' nutrition status (figure 63c). All three views are based on the average intake of the previous three days, excluding the current day. In addition to the immediate feedback, the users can see more detailed information on their history in the calorie screen and the statistics screen. The calories screen offers a combined overview of the caloric intake and the bonus calories gained through physical activity over the previous week (figure 63d). The statistics screen offers a visualization of the nutritional history per day, week, and month (figure 63e). Additionally, it shows the history of profile changes such as weight, PAL, BMI, or WHR. The visual feedback targets all types of decision making. While the statistics screen facilitates reflection on developments and trends in behavior, the home screen gives more immediate feedback tied to recent decisions. Finally, the visual feedback provided for each food item facilitates reflection while or even before the decision is made.

10.2.4 *Administration Features*

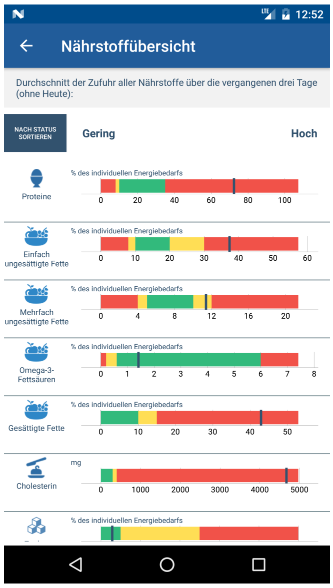
The administrative screens enable the users to configure their settings for the application. First of all, the login screen (figure 64a) is used to identify the user. Once logged in, the users can administer their application usage in the settings screen. Here, they can change their username and password or switch their physical activity tracking to a non-daily basis (figure 64b). In the profile screen (figure 64c), the users can furthermore update their characteristics, such as weight, height, hip measure, waist measure, and their personal goal. Finally, the preference screen (figure 64d) enables the users to exclude certain food items or food groups from their recommendations, to facilitate individual needs such as vegetarian, adherence to certain religious eating restrictions, or dislike of a specific ingredient. While the administrative screens provide only basic features, they are essential to personalize the user's system experience.



(a) The home screen shows visual recommendations for the sic most critical nutrients.

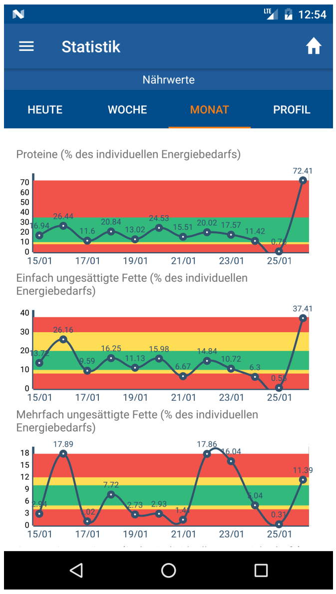


(b) The nutrient details view shows the diary data on one critical nutrient and lists connected food items.



(c) The nutrition status view shows the intake status of each nutrient based on the previous three days in the diary.

(d) The calorie overview shows consumed calories, calories burned during exercise, and the allowed calories according to the Basal Metabolic Rate (BMR)

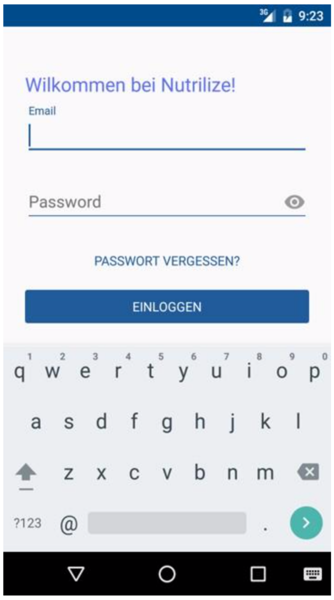


(e) The nutrient statistics view shows the full history of nutrient intake.

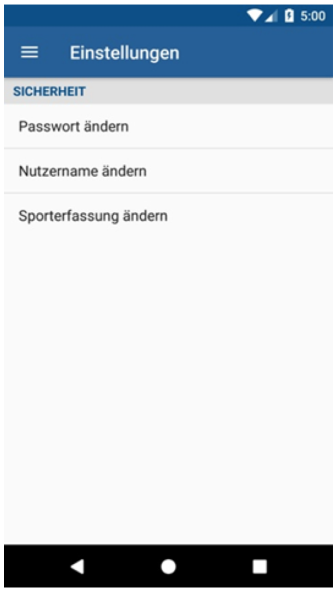
Figure 63: Different screens used for giving visual feedback in the *Nutrilize* prototype.

10.3 EVALUATION

To observe our final *Nutrilize* system in a real-life setting, we conducted a long-term user study wherein participants interacted with *Nutrilize* for 2-3 months during



(a) The login screen secures access to the application and the stored data.



(b) The settings screen allows changing the type of exercise assessment as well as the username and password.

(c) The profile screen summarizes the user data, explains blood values, BMI, and WHR values, and lets the users track their weight.

(d) The preference screen lets the user deselect food items or food groups (e.g. meat) that should not be included into the recommendations.

Figure 64: Different screens used for administrative tasks in the *Nutrilize* prototype.

which we captured their behavior with in-app tracking, repeated questionnaires, and interviews. The study uses both between-measures and within-measures and took place into two waves of participants with the following slightly adapted conditions. The first wave consists of 11 applications users and 11 control group users and lasts three months. The first wave is essential to assess the difference to a control group and to see the long-term effect for both groups. The application group of this wave could furthermore volunteer for an interview at the end of the study. The second wave consisted only of application users and had a duration of 2 months. Part of the second wave participants had previously conducted the first wave's control group and thus gave very detailed within-subject insights. The second wave of participants had to participate in an interview after four weeks and another after the full eight weeks. We expect the application group to show more improvements in their dietary behavior than the control group. We further expect the control group participants to improve even more when later participating in the applications. At the same time, we monitor the system interactions, the nutritional behavior, and several questionnaire-based outcome measures of all participants. We expect the interview data to give more background information and input on the causality of the quantitative analysis of the data.

10.3.1 *Study Procedure and Participants*

The study proposal was reviewed by the data protection commission of TUM (accepted on 9th of May 2017) and the ethics committee of the Klinikum Rechts der Isar (ID 477/16 S). The study is separated into four phases. The first phase is the screening process. Every participant had to complete a screening survey. If they fitted all the criteria, they had to send in their informed consent form. The second phase consisted of different surveys to collect the pre-study condition of the participants. The third phase consisted of 2-3 months of application usage or, in case of the control group, general nutritional advice via email. The third and final phase consisted of different surveys to collect the post-study condition of the participants. In the second wave, the participants additionally conducted interviews after four weeks and eight weeks. Table 19 shows the number of participants completing the different study measures in each group. The intervention group (I) was using the application for three months. Of the original 11 participants, 10 completed all pre-study measures, and 4 completed all post-study measures. Another 4 participants conducted a voluntary interview at the end of their study phase. The control group (C) was receiving general nutrition advice for three months. Of the original 11 participants, 9 completed all pre-study measures, and 8 completed all post-study measures. Of these 8 participants, 5 conducted the second wave of intervention after completing their study and used the application for another two months (CQ). Of these 5 participants, 3 conducted both interviews and the post-study measurements of the second wave. In addition to the control group participants, 12 new users were recruited for the second wave of intervention (Q). Of these 12, all conducted the pre-study questionnaires. Of this second wave group, 6 participants conducted the interview after four weeks, and 5 conducted all post-study measurements, including the final interview. None of the participants was paid for conducting the study. As a small reward, participants that conducted all measurements would receive a personal report on their nutritional behavior over the full study duration created by our *enable* (enable cluster, 2020) nutrition experts.

The participants were recruited using different articles and announcements in newspapers, such as the newspaper "Südddeutsche Zeitung" (Südddeutsche Zeitung

Table 19: Overview on number of measurements retrieved from different waves.

User Count	Group	Number of Months	FFQ Beginning	Baecke Beginning	Norman Beginning	Interview Middle	FFQ End	Baecke End	Norman End	Final Questionnaire	Interview End
11	I	3	10	11	11		5	5	6	4	4
11	C	3	9	9	9		9	9	9	8	
12	Q	1.75	12	12	12	6	8	8	8	5	5
5	CQ	2	5	5	5	3	3	3	3	5	3
39	All	2.49	36	37	37	9	25	25	26	22	12

GmbH, 2019), the local newspaper of Freising, an online article in the magazine "Ernährungsumschau" (Ernährungsumschau, 2019), and an article in the university's news media (TUM WZW, 2019). The screening was accessed by around 70 interested participants, of which around 40 finished the full screening survey. The screening excludes any participants that are minors, have food allergies or intolerances, suffer from illnesses, are influenced by diet (e.g., diabetes, liver, kidneys, lungs, heart disease, thyroid disease, anemia), are currently pregnant, are following a strict diet, have no Android device, or have no internet access. Any participants that passed the screening received the informed consent form. As discussed above, the final study was conducted by 34 of these participants who have each given their consent to the participation. Table 20 shows the demographics in each of the different intervention groups. As in previous studies (chapter 9, chapter 8), we have a strong bias towards female participants (29/34). The average age is higher than in the previous studies, with a maximum average of 41 in the intervention group and a minimum average of 33 in the qualitative group. The average BMI is very similar in the intervention and control group (around 29). The two qualitative groups have a slightly lower average BMI of 28 for the purely qualitative group and 26 for the participants that already did the control group. It is interesting to note that the control-qualitative group has the lowest BMI indicating either a bias of which people want to continue the study or the effects of the previous control intervention. Since the final questionnaire was only filled in by a part of the participants, the data on further user characteristics should be seen relative to this number. All the participants that filled in the final survey were of Caucasian ethnicity. The intervention group consisted only of full-time employees, while in the other groups, the split between full- and part-time jobs was almost 50/50. Also, the educational background is slightly different. While in the intervention group, three of the four final questionnaires indicate a university degree, less than half of the final questionnaires do so in the other groups. Of course, this comparison is strongly influenced by the dropout of participants before the final survey. The cooking survey gives much more homogeneous feedback: Almost all participants cook from base ingredients, and most are confident in cooking new foods. There is more variety concerning the frequency of cooking. While about half of the participants in the intervention group and the control-qualitative group are cooking 4-6 times per week, there are none that are doing so on the qualitative group, and almost all that are doing so in the control group. Finally, it is interesting to note that there are more participants confident in preparing new food than in eating new food. This difference might indicate that despite an overall high cooking ability and habit in the groups, the readiness to change habits is rather low.

Table 20: Participant characteristics in each study group.

User Count	Number of Interaction	Group	Number of Months	Age	Gender	BMI beginning	Final Questionnaire	Caucasian	Fulltime (yes)	Parttime (yes)	University Degree (yes)	Cooking from base ingredients (yes)	Cooking 4-6 times per week (yes)	Very confident to eat new food (yes)	Very confident to cook new food (yes)
11	18342.64	I	3	41.45	9	29.87	4	4	4	0	3	3	2	1	2
11	-	C	3	35	10	29.1	8	8	4	4	2	8	6	5	7
12	15503.5	Q	1.75	33.17	10	28.18	5	5	3	2	2	4	0	1	3
5	12383	CQ	2	35.8	5	26.48	5	5	2	3	2	5	2	3	4

10.3.2 *Data Collection*

We had five different measurement types in this study. An overview of all questionnaires used in this study is given in table 21. First, we measured the changes in physiology and eating behavior using three standardized questionnaires (Norman (Norman et al., 2001), Baecke (Baecke et al., 1982), FFQ (Food4Me Study, 2016b)). Second, we measured the users eating habits throughout the study using the app's dietary diary. Third, we measured the users' interaction with the system using the tracking tool Matomo, formerly named Piwik (Matomo, 2020). Fourth, we measured the users' subjective perception of the system (SUS (Brooke et al., 1996), SEM from chapter 9, their dietary change (based on (Shannon et al., 1997)), and their personality (Kaptein et al., 2009, Rammstedt et al., 2013). Finally, we interviewed the participants on their interaction, their system perception, their dietary change, their motives, and the effects of the application.

Table 21: Overview of variables assessed and questionnaires used in this study.

Scales and References	Values	Timing
Demographics	Age, Gender, Job, Education, Cooking	Pre and Post
Anthropometrics	Weight, Height, Waist, Hip, BMI, WHR	Pre and Post
Norman (Norman et al., 2001)	Physical Activity Level	Pre and Post
Baecke (Baecke et al., 1982)	Leisure, Work, and Sport Activity Index	Pre and Post
Food Frequency Questionnaire (FFQ) (Food4Me Study, 2016b)	Amount of Food Items, kCal, Nutrients	Pre and Post
Daily Tracking	Daily Amount of Meals, Food Items, kCal, Nutrients, Physical Activity	During
Logging	Screen, Action, Items	During
Dietary Change questionnaire (Shannon et al., 1997)	Fibre, Sugar, Fat, Salt, Fruit, Vegetables, Portion Size	Post
10-item Big Five Inventory (BFI10) (Rammstedt et al., 2013)	Neuroticism, Openness, Diligence, Extraversion, Compatibility	Post
Susceptibility to Persuasion Scale (STPS) (Kaptein et al., 2009)	Reciprocation, Scarcity, Authority, Commitment, Consensus, Liking	Post
Screens Liked	5 Point Likert Scale per Screen	Post
Helpful Screens	5 Point Likert Scale per Screen	Post
Perceived Usefulness (Venkatesh and Bala, 2008)	Score	Post
System Usability Scale (SUS) (Brooke et al., 1996)	Score	Post
Intention of Use and Payment	Yes/No, Payment Type, Payment Sum	Post
Visualization Screens	Understandable, Informative, Appealing, Unnecessary, Helpful, Learning, Helpful Changing, Motivating	Post
Recommender System Perception	Healthiness, Tastiness, Personalization, Diversity, Effort	Post
System Perception	Effort, Effectiveness, Choice Difficulty, Choice Satisfaction	Post

10.3.2.1 *Standardized Surveys on Nutrition and Physiology*

All participants had to fill out three standardized surveys at the beginning and the end of the study to be able to compare the changes. The first survey is a Food Frequency Questionnaire (FFQ) that covers the approximate intake of 150 typical food items over the past months. The items are connected to their nutritional information in the BLS, and each portion size (chosen by image) is recorded in grams. The standard portion size is used for items that are only rarely eaten to improve this survey's usability. The second survey is a Norman questionnaire that investigates the physical activity level of a person. In combination with the normal questionnaire, we also asked the users for repeated entry of their weight, height, waist circumference, and hip circumference. Finally, the Baecke survey gives a more detailed insight into the physical activity a user is doing in different aspects of their life, such as work, leisure time, and sports.

10.3.2.2 *Daily eating habits*

During the study, all the non-control group users were activity tracking their nutrition using our application. Therefore, we have measures of any food item being consumed, their portion size, and their nutritional values. Furthermore, we track which of the nutrients were focused on the home screen on the day an item was consumed.

10.3.2.3 *User Interaction*

Using the Matomo tool, we tracked the interaction with all the screens from the previous section. Additionally, we have the exact timing and duration of each interaction. Furthermore, we can extrapolate the number of interactions with each screen on a daily basis.

10.3.2.4 *Self-reported Measures*

In the final survey, after using our application, we ask the users several questions on their subjective perception. First, we ask about the perception of the system. Besides a rough estimate on the system's usability with a SUS questionnaire, we ask feedback on each application feature about their helpfulness and likability. We furthermore ask four questions on the impression of the overall perceived usefulness of the system (Venkatesh and Bala, 2008), and three questions about the intention of use in the future. Finally, we surveyed our users on nine subjective constructs. Five of these constructs focused on the perceptions of the recommendations: perceived healthiness (5 items, i.e. "the recommended recipes were relevant for my health"), perceived tastiness (4 items, i.e. "the recommended recipes fitted my taste preferences", perceived personalization (4 items, i.e. "the recommended recipes were well adapted to my eating habits"), perceived diversity (4 items, i.e. "the recommended recipes were very diverse"), and perceived effort of preparing (4 items, i.e. "the recommended recipes were hard to prepare"). Four constructs focused on the interaction with the system: system effort (5 items, i.e., "the *Nutrilize* app worked very easily"), system effectiveness (4 items, i.e., "With the app, I am able to make better dietary decisions"), choice difficulty (4 items, i.e., "Comparing the recommended recipes took a lot of effort") and choice satisfaction (5 items, i.e., "I am happy with the recipes I have chosen"). For all survey items, users indicated on 5-point Likert scales to what extent they agreed with them. While the questions are the same as in chapter 9 we cannot complete a Confirmatory Factor Analysis (CFA), due to the lower number in participants. Furthermore, we analyze each visualization's usefulness using 10 items (e.g., "The home screen helps me understand my personal nutrient status."). Second, we ask the users about their perceived dietary changes using a standardized dietary change questionnaire (based on (Shannon et al., 1997)). Third, we ask the user about their personal characteristics (e.g., job, education), their cooking habits (e.g., cooking type, cooking frequency), and their personality using a BFI10 questionnaire (Rammstedt et al., 2013) and a STPS with 12 items from Kaptein et al. (Kaptein et al., 2009) translated to German.

10.3.2.5 *Interview Data*

We conducted different semi-structured in-depth interviews with the participants. To cover the same topics in all of the interviews, we constructed interview guidelines for the mid-study interview and the end-study interview. For participants from the original study group that only conducted one optional interview at the end of the study, we used most of the mid-study interview guideline plus a number of questions to future system usage. The first interview guideline is split into four areas of interest. The first area covers eating motives with one block focusing on general eating motivation and the second block on changes in eating perception after using the application. The second area of interest covers nutrition changes with one block focusing on the actual changes and a second block focusing on difficulties and relapse patterns with these changes. The third area of interest covers the interaction with the application with one block focusing on interaction habits, one on the effect of the system components, one on difficulties with the system, one on the visualizations, and one on the recommendations. The final area covers either previous experience with nutrition application (mid-study of the qualitative group) or future usage of nutrition application (end-study of intervention group). Both variants focus on the comparison of *Nutrilize* with other applications and the pro and cons of either system. The second interview guideline is again split into four areas of interest. The first area covers eating motives and habits compared to the first interview with one block focusing on changes in eating perception after using the application and a second block focusing on difficulties and relapse patterns with the eating changes. The second area of interest covers the interaction changes compared to the first interview with one block focusing on interaction habits, one on the interaction motives. The third area of interest covers the study's perceived effects on nutrition knowledge, physical attributes, and psychological attributes. The final area covers the future usage of nutrition application with one block focusing on the *Nutrilize* system and one on other possible replacement systems. All interviews were fully transcribed. Afterward, a first run of coding the interview transcription was done using a deductive method with motives and categories derived from literature or the final survey data. Once all data was coded deductively, the second run of more detailed coding was done using the inductive methodology, by going through the text and refining the deductive motives/categories with the existent transcription. Appendix H shows a full list of deductive and inductive categories with an example sentence for each category.

10.3.3 *Results*

10.3.3.1 *Standardized pre-/post-study measures*

This section discusses the change measures pre- and post-study. Within this data, we only included those participants that have all measures covered. This restriction may also bias the analysis since only the motivated participants concluded all measures.

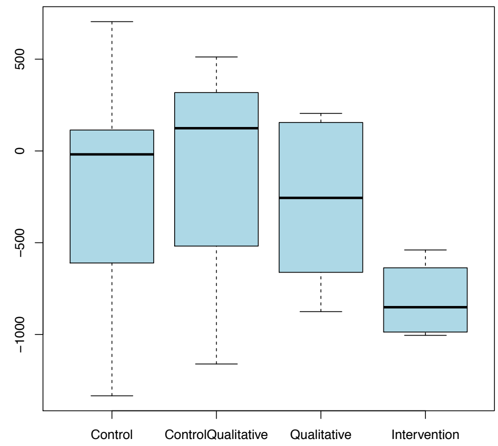
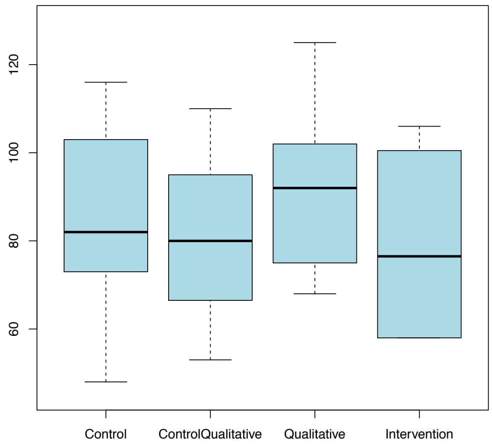
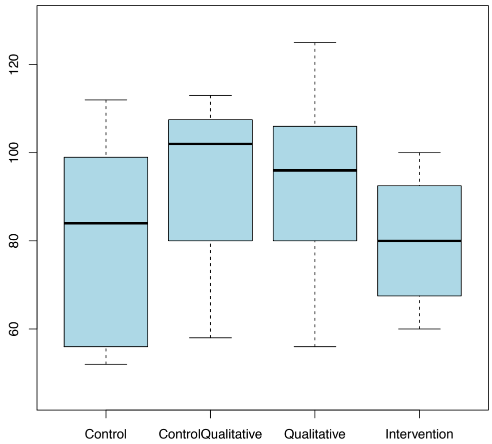


Figure 65: Difference in calories after the intervention in each group.

The first measure we focus on is the nutritional behavior derived from the FFQ data. We measured the changes between the beginning and end of the study regarding the nutrition with two variables, namely calorie intake and nutrient ability (as defined in chapter 9). For the calorie intake, figure 65 shows how the caloric intake decreased after the study, according to the FFQ. It is important to note that the FFQ, while being a standardized measure, still has a large error margin with energy being underestimated by 11-35% (Thompson and Subar, 2017). The strongest effect is visible in the intervention group that used the *Nutrilize* systems for three months. The weakest effects are visible in the control group and the control-qualitative group. Both groups show an average difference around 0, and a number of participants even increased their caloric intake. The qualitative group, which was using the application for two months, has a similar but weaker effect than the intervention group, with most participants reducing energy intake. The nutrition ability is calculated, as shown in chapter 9, by summing up the Rasch difficulty level of the six worst-performing nutrients of a certain user's FFQ. The minimal possible ability would thus be 21 and the maximal possible ability of 159. In the rare cases where less than six nutrients are critical, the scale is continued with fictional nutrients 24-29. Figure 66 shows both the initial ability spread, the final ability spread, and the changes in ability between the beginning and the end of the study. The user's abilities spread between 48 and 125 at the beginning of the study (figure 66a) and between 52 and 125 at the end (figure 66b). The difference between the pre- and post-measurement shows that the groups that interacted with the application have a low but positive average change in their ability. In contrast, the control group has a negative average change in their ability. However, the high fluctuation between individual participants and the low number of participants make a quantitative significance analysis of the effects impossible.



(a) Nutritional ability at the beginning of the study in each group.



(b) Nutritional ability at the end of the study in each group.

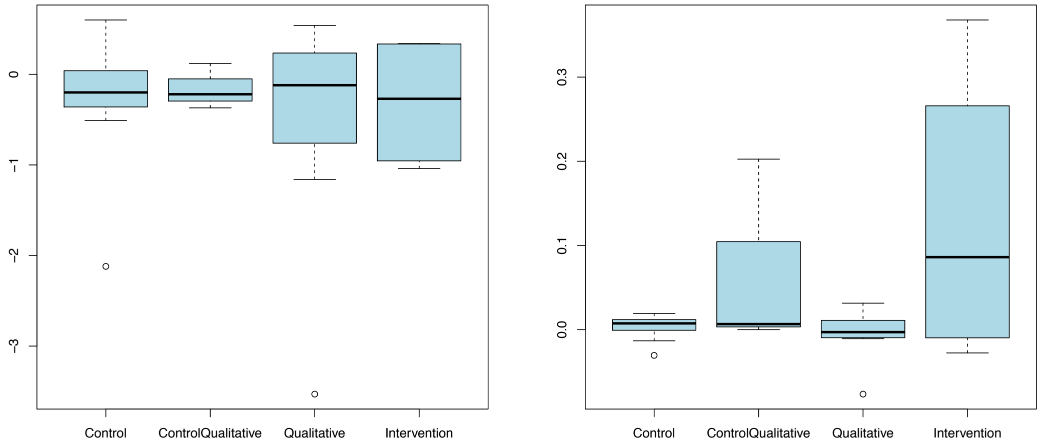
Figure 66: Nutritional ability over the study in each group

The second measure is the physical measurements BMI and WHR. Figure 67a shows the difference in BMI for the different groups after the intervention. All groups show a slight decrease in BMI on average. There are no great differences between the groups' average change. Figure 67b shows the difference in WHR for the different groups after the intervention. Most of the groups show almost no change in WHR. The intervention group even shows an average increase in WHR of 0.1.

The third measure is the physical activity collected from the Norman and Baecke questionnaires. Figure 68a shows the difference in PAL collected from the Norman questionnaire for the different groups after the intervention. Almost all groups have an average change of PAL around 0. Figure 68b shows the difference in the total Baecke index collected from the Norman questionnaire for the different groups after the intervention. Most groups show a slight increase in activity, while the intervention groups show a decrease on average. However, even in the intervention group the changes vary with some participants increasing their activity.

10.3.3.2 *Effects of the System on Nutrition Behavior*

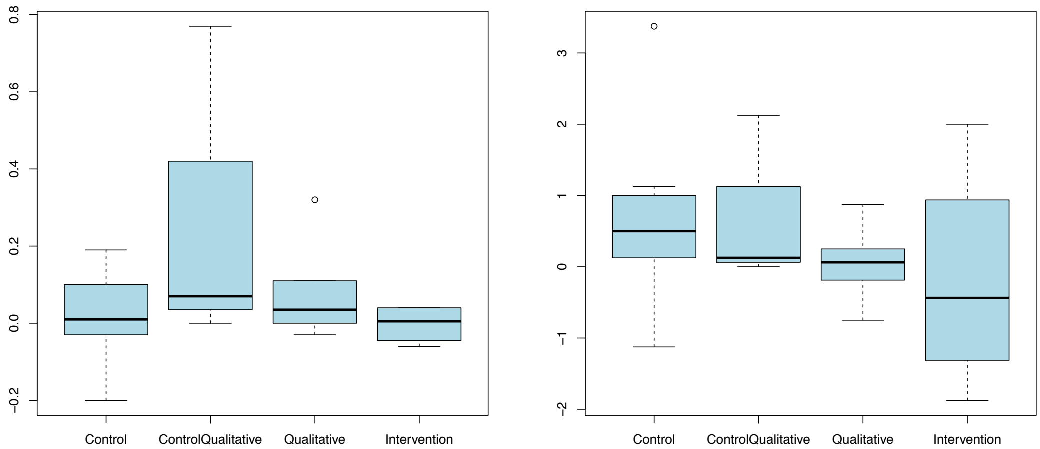
The daily nutritional data gives us a rich insight into the behavior of each user over a long-term intervention. First of all, we compare the caloric intake and the nutritional ability with the data from the standardized FFQ that we discussed in the previous section.



(a) Difference in BMI after the intervention in each group.

(b) Difference in WHR after the intervention in each group.

Figure 67: Physical markers over the study in each group.



(a) Difference in PAL after the intervention in each group.

(b) Difference in Baecke score after the intervention in each group.

Figure 68: Activity markers over the study in each group.

Figure 69 shows the caloric intake in both surveys and from the daily tracking tool. As in our previous studies (chapter 8), the caloric measurement is higher in both FFQs than in the daily tracking. The calories entered within the FFQ show a clear decrease between the beginning of the study and the end. The daily tracking is much more consistent over time with similar average intakes at the beginning and end of the study. However, the caloric intake seems to fluctuate strongly between days.

Figure 70 shows the nutritional ability of the users in both surveys and from the daily tracking tool. Except for three outliers, this ability is also higher in the two

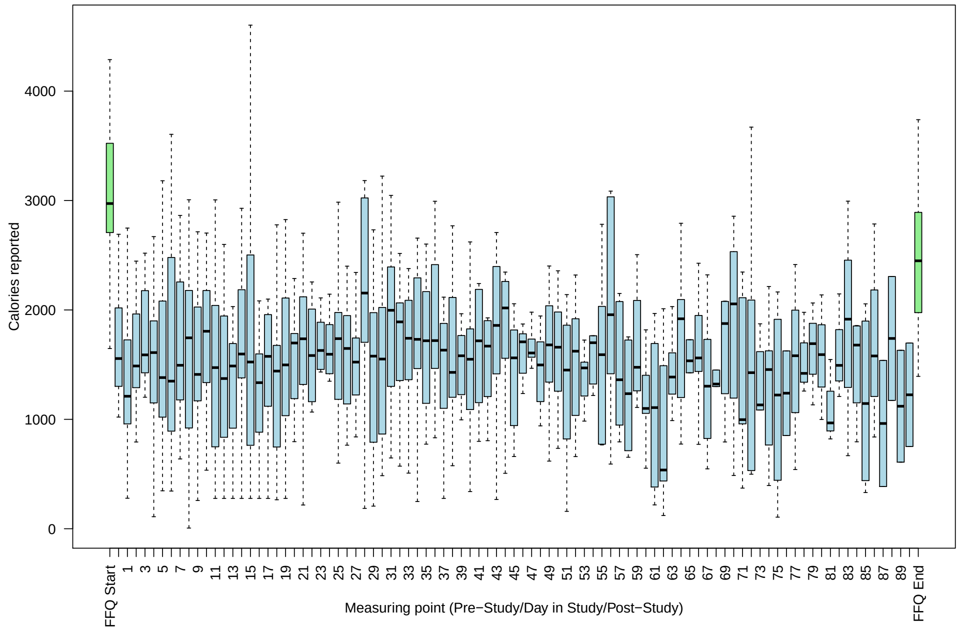


Figure 69: History of calorie consumption in the pre-study FFQ, during the study, and in the post-study FFQ.

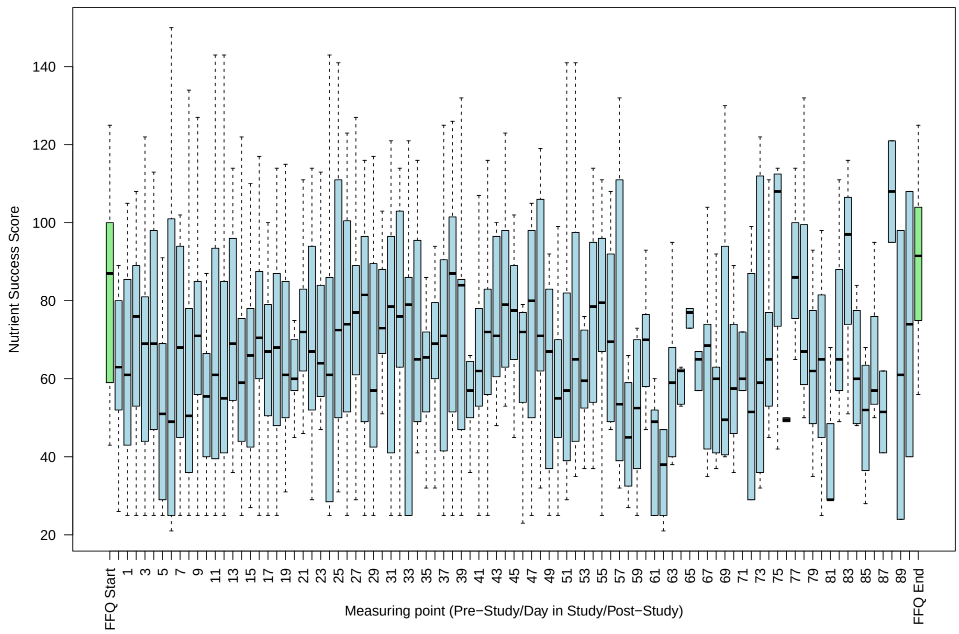


Figure 70: History of nutritional ability in the pre-study FFQ, during the study, and in the post-study FFQ.

FFQ surveys, than on a daily basis. As discussed in chapter 9, the nutrient intake is highly dependent on the caloric intake, which approximates the amount of food intake. Therefore, the difference in ability could be explained purely by the difference in caloric intake. The daily nutritional ability shows a higher fluctuation than the daily caloric intake. Furthermore, the fluctuation changes around day 60, when the groups in the 8-week qualitative phase stopped using the application, and the data only represents the 12-week intervention group or those participants that have not dropped out at that stage of the study. In this phase, we see the higher but also the lowest average performance, probably caused by the low sample number.

Since success depends on many other variables, as shown in chapter 9, we have a closer look at that dependence. Figure 71 shows an overview of all interdependent variables that influence nutritional success. The same visualization, as used in chapter 9 is used to analyze the short-term dataset. The first row and column show the distribution of nutrient measurements over time. We can see in the first column that the number of measures decreases over time. This decrease was not visible in the short-term dataset since it only covered the first 12 days, which are also quite homogeneous in this visualization. The first row, additionally shows that nutrients which have no determined focus are mostly appearing at the beginning of the study. This timing is reasonable since the NoFocus state only appears when there is a lack of data to determine the focus. Furthermore, in the first row of the third column, we see that the intervention group I uses the application longer than the qualitative Q and control-qualitative CQ group. This difference in duration is reasonable, since the group I had a study frame of 3 months while both other groups only had a predetermined study term of 2 months. Of course, both groups could use the application after the study's official end, which leads to measures beyond day 90. Finally, in the first row of the fourth column, we see that both successful nutrients and unsuccessful nutrients are equally distributed over time, indicating that the dropout does not influence or bias the success measurement. The second column and row show the interdependencies of the focused nutrients with the other parameters. It is important to note that the distribution of nutrients into different focus groups stays similar when changing time, groups, and calories. The only difference we observe is that unsuccessful nutrients are occurring more strongly in the focused nutrients. This bias of focused nutrients is expected since the algorithm determines the six worst-performing nutrients of the previous three days for the focus list. When considering the third/middle row and column focusing on the intervention group, the main differences are that the I group has an intervention of 3 months (visible in column one of row three), and the CQ group has previously participated in the control group of the first wave. The most interesting correlation is the one with the success of nutrients. Here we see that both qualitative and intervention groups achieve more successful than unsuccessful nutrients. The CQ group, however, has an almost even split between the two. For the last two columns and rows, it is most interesting to note that higher calories coincide with higher success rates, which we already suspected in the overview timelines. All other combinations with these two columns have previously been discussed in this section. In summary, this review of variables shows that the collected data behaves as expected and shows no measurement errors, inexplicable biases, or outliers. Such a sanity check is vital to the interpretation of the models built on this study's dataset. The observed correlations, such as higher calories and optimal nutrient intake, need to be integrated into such models as interaction effects.

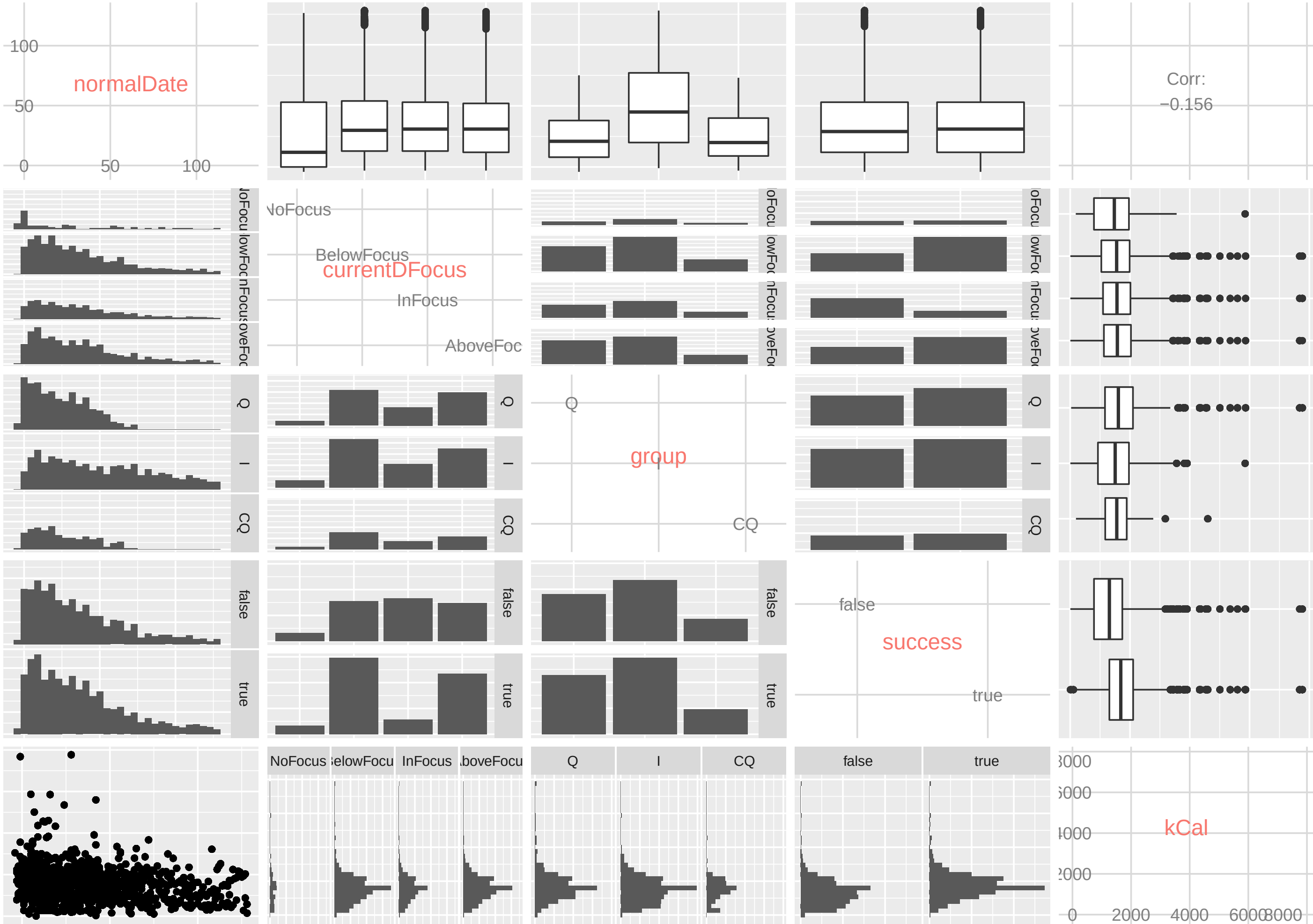


Figure 71: Overview of all variables influencing the successful consumption of nutrients.

To get a closer insight into the influence of the different parameters on the overall success, we build a multilevel logistic regression model (see table 22, such as in chapter 9. We observe that while for the short-term intervention, the application did not yet affect the nutritional ability over time, it does so in the long-term. First, we investigate the comparability of the two datasets, in order to exclude any bias given by the different country, different nutritional database, and different recipe dataset. Thus, we focus on the first 12 days of the dataset and compare the same model as in our short-term study chapter 9.

Table 22 shows the comparison of the short-term dataset and the first 12 days of the long-term dataset. Although the estimates are different in most cases, the variables show the same effect on the success in both models. Chapter 9 gives a detailed discussion of these influences and coefficients. One important difference is that while the recommendations were a significant factor in the Dutch study, they are not in the German study. Also, in both studies, the time factor was not significant during the first 12 days.

Now that we have shown the data behaves in a similar way, we extend the model to the full long-term study. We can immediately see that with the additional available data, all the factors of the model become highly significant ($p<0.001$). Thus, we can focus on the direction of the effects. The Rasch-scale is loosely represented in the tracked data, except for the fifth level that seems to be easier to achieve than expected. As discussed in chapter 9, it is also highly influenced by the caloric intake. Most importantly, the effect of time that was not visible in the short-term is now a strongly significant positive effect. Also, the recommendation interactions, as the representative for interactions in this model, is significant in the long term, but not in the short term. As our previous work (chapter 9) has shown, the recommendations itself may not be the best measurement of the interaction with the system since the system has such a multivariate influence with many more features intervening with the user's decision. Thus, the next chapter considers these features, the user's interaction with them, and their influence on the behavior change.

Table 22: Multilevel logistic regression with one random intercept for users and the successful nutrient intake as an outcome variable. For each model, the coefficient factor in the linear model, the Standard Error (s.e.), the z-value (coefficient divided by s.e.), and the p-value are given.

Fixed effects:		Extended	Model	IUI			12	day	model			Full	study	model	
	Estimate	Std	Z	Pr(>|z|)		Estimate	Std	Z	Pr(>|z|)		Estimate	Std	Z	Pr(>|z|)	
(Intercept)	1.60	0.18	9.02	<2e-16	***	1.32	0.22	5.97	0.000	***	1.34	0.12	10.94	<2e-16	***
nutrientLevel2	-1.85	0.08	-24.14	<2e-16	***	-1.08	0.15	-7.01	0.000	***	-0.85	0.07	-11.77	<2e-16	***
nutrientLevel3	-2.17	0.08	-27.35	<2e-16	***	-1.93	0.15	-12.87	<2e-16	***	-1.63	0.07	-23.46	<2e-16	***
nutrientLevel4	-2.64	0.09	-30.73	<2e-16	***	-1.88	0.15	-12.41	<2e-16	***	-1.62	0.07	-22.93	<2e-16	***
nutrientLevel5	-1.75	0.09	-19.87	<2e-16	***	-1.39	0.15	-9.21	<2e-16	***	-1.27	0.07	-18.32	<2e-16	***
calories	1.23	0.08	15.74	<2e-16	***	0.51	0.15	3.44	0.001	***	0.40	0.07	5.85	0.000	***
recommendations	0.08	0.02	4.21	0.000	***	0.06	0.04	1.53	0.125		0.09	0.02	4.81	0.000	***
rasch	-0.36	0.33	-1.09	0.274											
normalDate	0.001	0.01	1.63	0.103		0.06	0.04	1.44	0.150		0.16	0.02	7.41	0.000	***
todayBelowFocus	0.47	0.16	2.90	0.004	**	0.82	0.17	4.85	0.000	***	0.64	0.09	6.96	0.000	***
todayInFocus	-0.90	0.16	-5.51	0.000	***	-0.94	0.18	-5.20	0.000	***	-1.04	0.10	-10.87	<2e-16	***
todayAboveFocus	0.24	0.16	1.46	0.145		0.48	0.17	2.79	0.005	**	0.43	0.09	4.66	0.000	***
nutrientLevel2:calories	-0.66	0.09	-7.75	0.000	***	0.56	0.18	3.15	0.002	**	0.74	0.09	8.60	<2e-16	***
nutrientLevel3:calories	-0.26	0.09	-2.95	0.003	**	0.21	0.17	1.27	0.204		0.32	0.08	4.02	0.000	***
nutrientLevel4:calories	-0.16	0.09	-1.79	0.073	.	0.43	0.17	2.44	0.015	*	0.64	0.08	7.62	0.000	***
nutrientLevel5:calories	-1.35	0.08	-16.00	<2e-16	***	-0.64	0.16	-3.92	0.000	***	-0.56	0.08	-7.41	0.000	***
rasch:normalDate	0.03	0.01	2.71	0.007	**										
todayBelowFocus:rasch	0.45	0.32	1.40	0.163											
todayInFocus:rasch	0.86	0.33	2.63	0.009	**										
todayAboveFocus:rasch	-0.32	0.32	-0.98	0.329											

10.3.3.3 *Long-term system interaction*

Besides the daily dietary and nutrient intake from the tracking tool of our application, we have also tracked the interactions with the system over time. Our previous work (chapter 8) shows that the most time-consuming activities are tracking interactions. Therefore, we analyze the interactions on a high level and zoom down into the detailed feature interactions.

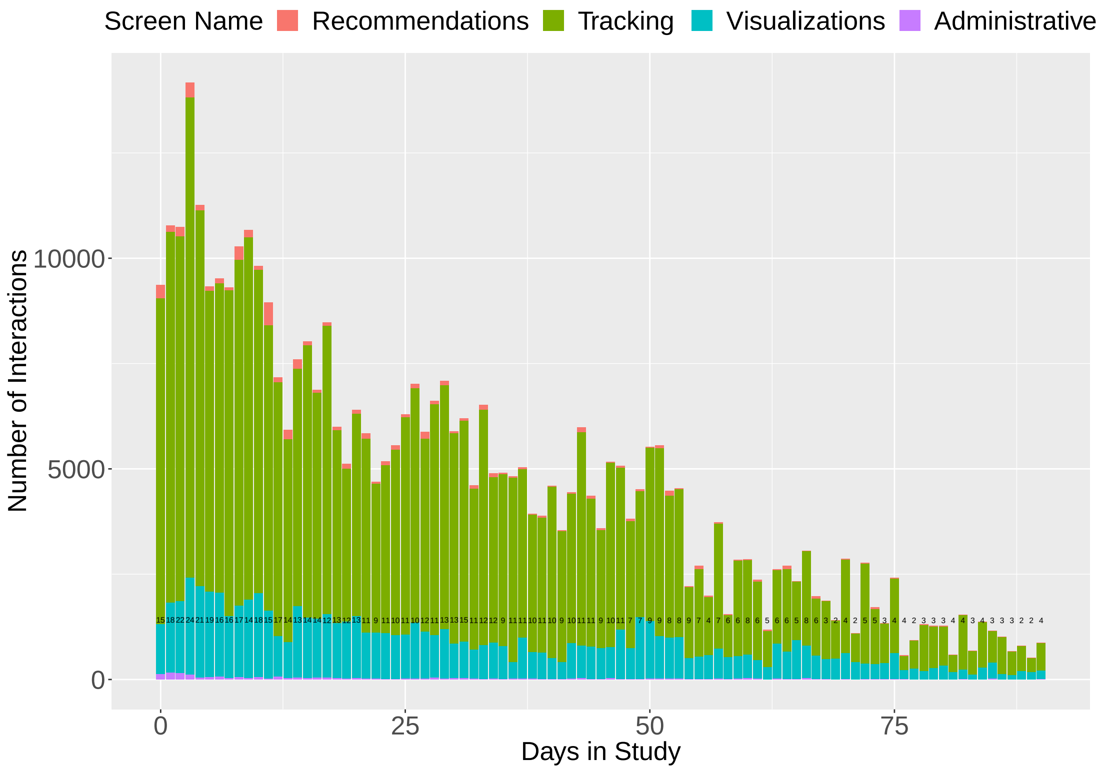


Figure 72: History of interactions during the study on a summarized level, including tracking actions. The numbers on each bar indicate individual users on a specific day.

Figure 72 shows an overview of the high-level interaction types: Tracking, Recommendations, Visualizations, and Administration. Each of these categories summarizes the number of interactions with these screens that were tracked in the systems. The first thing to note is the continuous decrease of interactions over time. This decrease behaved differently for the types of activities. While the visualization interactions decrease very slowly, the tracking activity increases drastically. The recommendation interactions stay on a similar level over the first weeks but then decrease into almost no interaction. The administrative screens have most of their interactions in the first week, which is to be expected due to their functionality. Furthermore, as in our short-term dataset (chapter 8), the tracking interactions make out the large majority of interactions.

To get a closer look into the distribution of feature usage, we exclude all tracking interactions in figure 73. As shown in our previous work (chapter 8), the statistics screen has the most interaction of all features. Considering the long term changes in interactions, we can also see that the statistics screen is one of the few to be still used

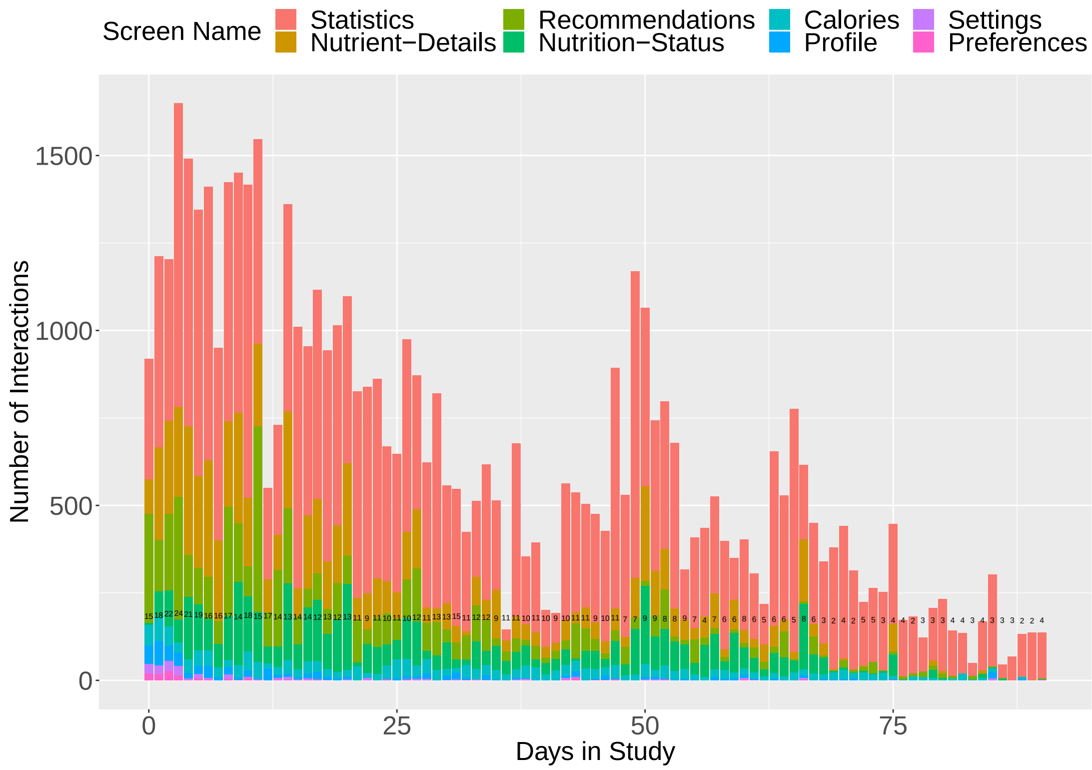


Figure 73: History of interactions during the study on a detailed level excluding tracking actions. The numbers on each bar indicate individual users on a specific day.

at the end of the study. It is also interesting to note that while the tracking activity decreased in a very continuous manner, the feature usage has more fluctuation in the number of interactions. From the other visualizations, the nutrient-details and the nutrition status, which are both accessible over the home-screen visualization, have the strongest number of interactions and even a long persistence over time, while the calorie visualization is of minor importance. The administrative screens decrease very quickly after the start of the study. The only screen with longer activities is the profile screen, where users can enter changes in weight and other body measures. Finally, the recommendations have a fair share in interactions at the beginning of the study but quickly decrease into a minor percentage of the interactions around the middle of the intervention.

To see which screens the users liked to interact with most and which screens finally influenced the users' nutritional behavior, we excluded the interactions of the current day into the previous multilevel logistic regression model on nutrition success. Table 23 shows the results of these models. As with the visual insight, we derived a high-level model and further moved into a model considering each screen. The first thing to note is that all the previous effects of the nutrition Rasch-level, the calories, and the nutrient focus have stayed similar to the previous model. In the high-level model, we see that while the tracking and visualization screens have a positive impact on the nutritional behavior, the recommendations have no significant impact in either direction and the administrative features even have a negative impact on the nutritional success.

Table 23: Extended multilevel logistic regression with one random intercept for users and the successful nutrient intake as an outcome variable, including interaction categories. For the model, the coefficient factor in the linear model, the Standard Error (s.e.), the z-value (coefficient divided by s.e.), and the p-value are given.

Fixed effects:	Extended	Model	Full	Study	Interactions
	Estimate	Std	Z	Pr(>|z|)	
(Intercept)	1.61	0.12	13.35	<2e-16	***
nutrientLevel2	-0.86	0.07	-11.92	<2e-16	***
nutrientLevel3	-1.65	0.07	-23.62	<2e-16	***
nutrientLevel4	-1.63	0.07	-23.10	<2e-16	***
nutrientLevel5	-1.28	0.07	-18.40	<2e-16	***
calories	0.37	0.07	5.50	0.000	***
normalDate	0.18	0.02	8.44	<2e-16	***
todayBelowFocus	0.43	0.09	4.62	0.000	***
todayInFocus	-1.26	0.10	-12.69	<2e-16	***
todayAboveFocus	0.23	0.09	2.43	0.015	*
recommendations	0.02	0.02	0.84	0.402	
tracking	0.19	0.02	7.76	0.000	***
visualizations	0.18	0.03	7.09	0.000	***
administration	-0.11	0.02	-5.38	0.000	***
nutrientLevel2:calories	0.73	0.08	8.61	<2e-16	***
nutrientLevel3:calories	0.33	0.08	4.15	0.000	***
nutrientLevel4:calories	0.64	0.08	7.76	0.000	***
nutrientLevel5:calories	-0.55	0.07	-7.37	0.000	***

The second model is shown in table 24 allows us to refine these findings. Since the recommendation interactions are not further distinguished, they still have no significant effect on the behavior. Regarding the tracking interactions, the screens responsible for the positive impact on nutritional behavior are the food-search and the food details. This result is expected since the food search indicates a diligent tracking and thus well adjusted nutritional information for the model. In contrast, the food details might even indicate a planning/decision process during the tracking action. From the visualization screen, the most influential scenes are, in line with the number of interactions, the statistics screen, and the home screen. The responsible screens for the negative influence of the administrative interactions are the login and profile screen. This negative correlation might be explained by the login screen showing up after an application crash and thus signifying technical problems. This insight leads us to the next question of how the users perceived the screens, which we have shown to be both popular and influential. Thus, the following section shows the system perception that we examined during the final survey.

Table 24: Extended multilevel logistic regression with one random intercept for users and the successful nutrient intake as an outcome variable, including interaction details for each screen. For the model, the coefficient factor in the linear model, the Standard Error (s.e.), the z-value (coefficient divided by s.e.), and the p-value are given.

Fixed effects:	Extended Estimate	Model Full Std	Study Z	Detailed Pr(>|z|)	Interactions
(Intercept)	1.61	0.12	13.19	<2e-16	***
nutrientLevel2	-0.86	0.07	-11.93	<2e-16	***
nutrientLevel3	-1.65	0.07	-23.64	<2e-16	***
nutrientLevel4	-1.63	0.07	-23.10	<2e-16	***
nutrientLevel5	-1.28	0.07	-18.41	<2e-16	***
calories	0.35	0.07	5.18	0.000	***
normalDate	0.18	0.02	7.98	0.000	***
todayBelowFocus	0.48	0.10	5.01	0.000	***
todayInFocus	-1.22	0.10	-12.10	<2e-16	***
todayAboveFocus	0.28	0.10	2.87	0.004	**
Recommendations	-0.03	0.03	-1.04	0.299	
Food-Search	0.09	0.04	2.56	0.011	*
Food-Details	0.15	0.05	3.24	0.001	**
Diary	-0.01	0.03	-0.40	0.690	
Sport-Search	0.05	0.03	1.83	0.068	.
Statistics	0.10	0.03	3.86	0.000	***
Home	0.12	0.04	2.90	0.004	**
Nutrient-Details	-0.03	0.04	-0.65	0.516	
Nutrition-Status	0.05	0.04	1.24	0.216	
Calories	0.03	0.02	1.30	0.194	
Login	-0.05	0.02	-2.69	0.007	**
Profile	-0.05	0.02	-2.15	0.031	*
Settings	-0.02	0.02	-0.98	0.328	
Preferences	-0.03	0.02	-1.45	0.146	
nutrientLevel2:calories	0.72	0.08	8.58	<2e-16	***
nutrientLevel3:calories	0.32	0.08	4.12	0.000	***
nutrientLevel4:calories	0.64	0.08	7.74	0.000	***
nutrientLevel5:calories	-0.55	0.07	-7.39	0.000	***

10.3.3.4 *Perception of the system after long term usage*

System perception was part of our final survey. Since we can only examine the survey by the participants that both finished the survey and used the application, the number of samples is reduced to 12.

Table 25: Popularity of screens on a 1-5 Likert scale.

User Count	Group	Home Screen	Nutrient Status	Nutrient Details	Calorie Overview	Sports Search	Food Search	Nutrient Preview	Nutrient Full Preview	Diary	Recommendation	Statistics	Profile	Preferences
4	I	3.5	3.25	3.67	4	2.33	2.5	3	3.75	3.75	2	5	3.33	3
5	Q	4	4.6	4.2	3.75	2.8	2.6	3.6	3.8	3.2	3.2	4.4	4	3
3	CQ	4.67	4.67	3.67	4.67	3.33	3.33	4	3.33	4.33	2	3.67	4.67	2.33
12	All AVG	4	4.17	3.91	4.1	2.82	2.75	3.45	3.67	3.67	2.55	4.36	4	3.08
12	All Min	2	2	3	3	1	1	2	2	2	1	3	3	1
12	All Max	5	5	5	5	4	4	5	5	5	5	5	5	6

First, we look at the popularity of the different feature screens. In the previous sections, we showed that the statistics and the nutrient overview and details, reachable over the home screen, are the most used screens. During the survey, the users gave ratings on a 1-5 Likert scale shown in table 25. We see that the same screens that influenced nutrient success are also reaching ratings around 4. Additionally, the calorie overview and the profile were liked, but not used that often. The recommendations were the least popular feature, which might explain the difference in impact between the model of this study's first 12 days and the Dutch dataset.

Table 26: Helpfulness of screens on a 1-5 Likert scale.

User Count	Group	Home Screen	Nutrient Status	Nutrient Details	Calorie Overview	Sports Search	Food Search	Nutrient Preview	Nutrient Full Preview	Diary	Recommendation	Statistics	Profile	Preferences
4	I	4.75	4	3.67	3.67	2	2.67	2.67	3.75	4	1.67	4.67	3	2.67
5	Q	4.6	4.2	3.8	3.5	3	3.4	3.4	3.4	4	3.2	3.8	3.2	2.2
3	CQ	5	4	3	4	3	2.67	2	2.33	4.33	1.67	3.33	3.33	2.33
12	All AVG	4.75	4.09	3.55	3.7	2.73	3	2.82	3.25	4.08	2.36	3.91	3.18	2.36
12	All Min	3	3	2	2	1	1	1	1	3	1	3	2	1
12	All Max	6	5	5	5	5	5	5	5	5	5	5	5	4

Second, we look at the perceived helpfulness of the different screens. In the previous sections, we showed that the most influential positive screens were the statistics, home-screen, and the food-details within the food-search. During the survey, the users gave the following ratings on a 1-5 Likert scale (Table 26). The home screen and the statistics have high ratings, confirming their helpfulness. Instead of the food-search and food-details, the users perceived the diary as helpful, which had no significant effect in our model. Furthermore, the nutrient overview was perceived as helpful but had no significant effect in our model.

Table 27: Quality assessment of visualization screens with a combination of several items on a 1-5 Likert scale.

User Count	Group	Home Screen	Nutrient Status	Nutrient Details	Statistics	Nutrient Preview	Nutrient Full Preview
4	I	3.83	3.97	3.1	4.6	3.43	4.03
5	Q	4.15	4.45	4.33	4.3	3.88	3.68
3	CQ	4.27	3.97	3.77	3.9	2.8	3.07
12	All AVG	4.09	4.16	3.79	4.27	3.42	3.6
12	All Min	3.3	3.5	2.1	3.7	1.1	2.1
12	All Max	4.7	4.7	4.6	4.8	4.9	5

Third, we take a closer look at the visualizations and how they were perceived. The users answered several questions to each visualization about understandability, helpfulness, and similar items. The overall scores are shown in table 27. As indicated in the previous measures, all the screen received excellent feedback with the highest rating going to the home screen, the nutrient overview, and the statistics screen.

Table 28: Quality assessment of recommendations aspects with a SEM questionnaire.

User count	Group	Health	Taste	Diversity	Personalization	Difficulty	System Effort	System Effectiveness
4	I	2.55	2.5	3.56	2.5	2.33	3.1	4
5	Q	3	2.9	3.5	2.4	3.15	3.16	3.65
3	CQ	2.53	2.25	3.42	2.83	3.42	3.2	4
12	All AVG	2.73	2.6	3.5	2.54	3	3.15	3.84
12	All Min	2.2	2	2.75	2	2.25	1.6	3
12	All Max	3.8	3.25	4.75	3.25	4	4.4	4.75

Fourth, we look at the recommendations and how they were perceived (table 28). For this, we used the same SEM questionnaire as in chapter 9. The highest positive feedback was given to diversity and overall system effectiveness. Indecisive feedback was given to the difficulty of the recommendations and the system effort, with an average of 3 and a high deviation in answers. Health, taste, and personalization were all graded slightly negatively by using values around 2.5 on a scale of 1-5. These constraints might explain the overall negative feedback on the recommendations.

Table 29: Participant feedback on the overall quality of the application.

User count	Group	SUS Score	App gives overview on diet	App improves diet	App eases a healthy diet	App is a useful tool	Would buy app	Payment of 2-5€	Payment Type
4	I	55.63	3.25	3	3.25	3.25	1	0	0
5	Q	58	3.8	3.4	3.4	3.2	3	2	2
3	CQ	65.83	5	3.33	3.67	4	2	2	2
12	All AVG	59.17	3.92	3.25	3.42	3.42	6	4	4
12	All Min	30	1	1	1	1	N	<2€	Once
12	All Max	77.5	5	5	5	5	Y	5-10€	Abo

Finally, we asked users for feedback on the overall application and their intention to further use it (table 29). The SUS score of 59 is lower than in the first usability test but higher than in the pilot study (chapter 8), which indicated that the improvements were effective. The users agree the strongest to the application giving them insights into their diet. The users agree slightly to the app being a useful tool and making it easy to eat healthily. The least agreement is to the fact that the application improved the diet. This opinion is in line with the standardized measures before and after the study that showed little effect on visible measures but some effect on the nutrient intake, which would be less tangible. Overall, half of the survey participants would buy the application. Most of them would agree to pay a one time fee of 2-5€.

To summarize, the popularity of screens is mostly in line with the relative usage of these screens. The helpfulness has discrepancies in the actual influence of the screens on the user's nutrition. The visualizations are perceived very well, while the recommendations struggle to attract the users. Since these numbers cannot tell us anything about the reasons for these perceptions and the previously detected interaction and nutrition patterns, the next section discusses the additional qualitative analysis of the semi-structured in-depth interviews.

10.3.3.5 *Contexts and motives from interview data*

This section elaborates on the different areas of interest from the interview datasets. The order of topics is aligned with the previous sections. This section analyzes the coded information from the qualitative analysis. An example sentence for each factor is given in appendix H. First, we gain deeper insights into our target group. We analyze the users' motives combined with information on their demographics and their personality type (Rammstedt et al., 2013, Kaptein et al., 2009), from the final survey. Second, we look into the effects of the application. We analyze the interview data on their perceived physical, psychological, and cognitive changes combined with standardized change measures discussed in the first results section. Third, we look into the users' dietary change and their perception of it. We analyze the interview data on their nutrition changes and their difficulties combined with the dietary change questionnaire (based on (Shannon et al., 1997)) from the final survey. Fourth, we look into the users' interaction patterns. We analyze the interview data on their interaction habits and their system feedback combined with their aggregated interaction patterns. Fifth, we take a deeper look into the application perception and intention of use by analyzing the interview data on comparing the application to previous or future systems.

Table 30 shows insights into the user's motives and personality types. If a participant has filled this survey, twice the results were averaged. The first interview block focusses on the motives of each participant for eating. The most prominent motives are habit (7/13) hunger (5/13) and appetite (5/13), closely followed by stress (4/13). More specific motives that were named might not apply to all participants, such as family (3/13), regular mealtimes (3/13), and time (2/13). Regarding the health aspect of eating, (2/13) participants considered the health effect of their food and (3/13) regarded food more generally as a means of survival. Finally, three motives were only mentioned by individual participants such as tradition (1/13), social norms (1/13), and good looks (1/13). The second and third block asked the participants for changes in their eating perception since starting to use the application. The second block focusses on the responses mid-study (after four weeks) and the third block on the responses at the end of the study (8 or 12 weeks). In the middle of the study, the majority of interviewees (5/8) state they do not feel constrained in their eating behavior by the applications. Of the things they did perceive more prominently, they report mostly on regrading food items (5/8) that could be exchanged. To some smaller extend, they report considering which nutrients they might be missing (2/8) and developing a better intuition about portion sizes (2/8). Further individual responses were the difficulty of tracking their intake (1/8), the influence on social behavior (1/8), and enhanced pleasure when eating (1/8). At the end of the study, many participants (5/12) still do not feel constrained by using the application. Furthermore, the number of participants that report enhanced pleasure when eating increased to (4/12). Other concepts such as increased awareness on the food item choice (4/12) and nutrient coverage (3/12) stayed important, while portion sizes lost in attention (1/12). Two new aspects mentioned are thoughts about weight loss (3/12) and calories (2/12). The high effort of racking the intake (1/8) and the influence on social behavior (1/8) remained as minor aspects. Finally, one participant mentioned feeling regret when eating against her plans.

Table 31 shows the data on the application effects and the BMI and ability measurements. This interview data was only part of the second interview, and this not performed by all participants. The first interview block focusses on knowledge about nutrition gained throughout the study. Most common learnings are about their own nutritional needs (4/8) and the nutritional content of food items (4/8). Three participants (3/8) even gained transfer knowledge on which food items to include in their daily habits. These three participants have furthermore all increased their nutritional ability (3/4). Further insights that were named are portion sizes of food and own portion/calorie requirements. These concepts were named by the two users who already had very high nutritional abilities before the intervention. The second block focusses on physical changes. The feedback on this question is very diverse. (2/8) participants report weight loss, although only one of the shows significant BMI changes. (2/8) participants report no changes at all, although one of them has increased the nutritional ability and lowered the BMI by 1. (3/8) participants report increased physical activity, with (2/3) of them additionally reporting wellbeing and (1/3) reporting wellbeing in combination with less tiredness (1/8). Finally, (2/8) participants reported watching and holding their weight, which is reasonable in these cases since they are the participants with the lowest BMIs (normal weight). The last block focusses on psychological changes. This question was difficult to understand for a number of participants, so the results should be considered with care. Most participants report no changes or changes that are caused by other external factors (5/8). Most other participants report being annoyed by the tracking (4/8). Interestingly, (3/4) of these reports of being annoyed also reported feeling more empowered and enabled by the application. Other mentions include being in a good mood (1/8) and being content (1/8).

Table 30: Qualitative evaluation of user's motives and personality.

Codes	Group	Reciprocation	Scarcity	Authority	Commitment	Consensus	Liking	Extraversion	Neuroticism	Openness	Diligence	Compatibility	Habit	Appetite	Hunger	Stress	Family	Survival	Health	Time	Appearance	SocialFactors	Tradition	FoodItems	NoConstraints	Nutrients	Portions	EffortTracking	Pleasure	Socialbehavior	NoConstraints	FoodItems	Pleasure	Nutrients	Weight	Calories	EffortTracking	Socialbehavior	Portions	Regret
													Tell us why you eat											Tell us how your perception of eating has changed							Tell us how your perception of eating has changed									
35	I	4.0	2.0	3.0	4.0	3.0	3.0	3.0	3.0	4.0	3.0	3.0	●		●							●									●	●	●			●				
35	I	4.0	4.0	2.0	4.0	2.0	4.0	1.0	2.0	2.0	4.0	4.0			●	●		●	●												●		●		●					
32	I	4.0	4.0	3.0	4.0	4.0	4.0	4.0	3.0	5.0	4.0	4.0		●		●			●													●	●	●		●	●			●
28	I												●	●	●		●	●														●					●			
50	Q	3.0	4.0	3.0	4.0	3.0	3.0	4.0	2.0	3.0	4.0	3.0	●	●				●						●	●	●								●						
44	Q	4.0	4.0	4.0	4.0	3.0	3.0	3.0	2.0	4.0	4.0	2.0		●	●											●				●				●				●		
40	Q																●			●				●	●		●		●		●							●		
31	Q														●	●				●				●																
35	Q	3.0	3.0	2.0	4.0	3.0	3.0	3.0	3.0	2.0	3.0	3.0				●											●	●							●					
31	Q	4.0	3.0	3.0	5.0	3.0	3.0	3.0	2.0	1.0	4.0	3.0	●	●																					●					
57	CQ	2.0	3.25	3.0	4.0	3.0	3.25	3.75	2.0	2.0	4.0	3.0	●												●						●								●	
42	CQ	3.25	2.75	3.25	4.0	2.75	3.25	2.25	2.75	4.0	4.0	2.0	●				●				●		●	●	●							●	●							
44	CQ	3.0	3.75	3.0	4.25	4.0	3.25	4.0	2.0	2.0	3.25	3.75	●											●	●						●									

Table 31: Qualitative evaluation of user's changes in nutrition, physique, and mentality.

Codes	Group	Ability To	BMI To	Ability Tend	BMI Tend	NutrientRequirement	NutrientsInFood	FoodItemsInDiet	CalorieRequirements	PortionSizeFoodItemsf	MorePhysicalActivity	Wellbeing	LooseWeight	UnchangedOrDueToExternalReasons	WatchWeight	Tiredness	UnchangedOrDueToExternalReasons	Annoyance	AbilityToAct	GoodMood	Satisfaction
						Tell us how your nutrition knowledge changed					Tell us how you changed physically						Tell us how you changed mentally				
50	Q	91	29.03	103	28.67		●	●				●				●	●				
44	Q	103	24.69	125	23.53		●							●				●	●		
40	Q	125	27.12	105	27.12									●			●				
31	Q																				
35	Q	72	35.27	85	31.74	●	●	●					●				●				
31	Q	101	21.8	56	21.19	●	●								●			●	●		
57	CQ	116	24.62	110-113	24.46-24.09	●			●		●		●				●	●		●	
42	CQ	103	22.66	80-102	22.46-22.58	●					●	●			●		●				
44	CQ	48	27.17	53-58	26.66-26.44			●			●	●						●	●		●

Table 32: Qualitative evaluation of user's challenges concerning nutrition changes.

Codes	Group	Has Changed Fibre	Has Changed Sugar	Has Changed Fat	Has Changed Fish	Has Changed Salt	Has Changed Fruit	Has Changed Vegetables	Has Changed Portion Sizes	Vegetables	Fruit	LessPortions	Fibre	Balanced	FattyAcids	NoChange	Sugar	Carbohydrates	Hunger	Nuts	Salt	TraceElements	Vegan	Time	NoDifficulties	Effort	FavoriteFood	SocialFactors	NewHabits	Work	Events	Holiday	Illness	Weekend	SocialFactors	Effort	Helplessness	NewHabits	NoDifficulties	Restaurant	Events	FavoriteFood	Reduction	KnowledgeGain
										Tell us how you changed your nutrition															Tell us how you will sustain your changes										Tell us how you will sustain your changes									
35	I	4.0	1.0	4.0	2.0	4.0	1.0	4.0	4.0	●		●	●				●					●															●					●		
35	I	2.0	5.0	5.0	2.0	2.0	4.0	3.0	5.0	●	●								●	●																			●	●		●		
32	I	5.0	5.0	1.0	5.0	1.0	3.0	3.0	3.0					●			●																					●		●	●			
28	I									●	●							●																	●	●								
50	Q	2.0	2.0	3.0	3.0	2.0	3.0	3.0	4.0			●		●																				●			●							
44	Q	4.0	4.0	4.0	1.0	2.0	4.0	4.0	4.0	●	●														●	●				●							●							
40	Q											●	●													●	●	●			●				●			●			●			
31	Q									●		●	●										●				●																	
35	Q	4.0	4.0	4.0	4.0	4.0	4.0	4.0	5.0			●												●	●			●		●					●	●							●	
31	Q	2.0	4.0	2.0	2.0	2.0	5.0	4.0	5.0		●					●									●											●								●
57	CQ	2.0	4.0	3.0	3.0	4.0	4.0	4.0	4.0	●	●	●			●											●	●	●	●						●					●				
42	CQ	3.0	3.0	3.0	3.0	3.0	4.0	4.0	3.0						●	●									●														●				●	
44	CQ	2.0	1.0	3.0	1.0	1.0	5.0	2.0	4.0	●	●										●								●			●	●					●	●					

Table 32 shows the dietary change questionnaire and the interview insights on the difficulties and successes with dietary change. If a participant has filled this survey, twice the results were averaged. The first block focuses on the type of dietary change that the participants where targeting. The three most important changes are eating more vegetables (7/13 and 3.6), eating more fruits (6/13 and 3.5), and eating less food in general (6/13 and 4.1). All three also show very high average responses in the results from the dietary change questionnaire. However, during the survey, reducing sugar was reported in similar strength (3.6) to these three points, but it only rarely reported during the interview (2/13). Other changes were reported less in both the interview and the survey, such as increasing fiber (3/13 and 3.2), reducing fat (2/13 and 3.3), and reducing salt (1/13 and 2.6). Although the intake of fish was reported in the questionnaire (2.8), none of the participants mentioned it. Beyond the standardized survey, the interviews gave new ideas on what the participants are focussing on. (2/13) participants were trying to eat more balanced. Other ideas were only brought up by single participants (1/13) such as avoiding ravenousness, eating vegan, eating low carb, increasing nut consumption, focussing on trace elements, and eating at a different time. Finally, (2/13) participants were claiming to not have changed anything but at the same time reported something they had considered. The second and third block focus on how these changes are sustained over time. The second block covers answers in the middle of the study after four weeks of application usage and the third block at the end of the study (eight or twelve weeks). In the middle of the intervention (after four weeks), the most common reasons for relapse were favorite food items (3/9), social factors (3/9), and general high effort (3/9). Other important factors are the participants' work (2/9) and different types of extraordinary situations such as events (1/9), illness (1/9), holidays (1/9), and weekends (1/9). When taking all these single responses together, extraordinary situations are a major disturbance (4/9) to diet changes. At the same time, the feedback to the changed behavior was mostly positive. Almost half of the participants reported having no difficulties or considering their issues minor (4/9), and two even claimed to have established new habits (2/9). The third block questions the participants for relapses and difficulties at the end of the study (either after 8 or 12 weeks). There is still positive feedback with (3/12) reporting to have no major issues and (3/12) reporting to have established new habits. The relapse reasons are also similar, even if a little shifted, with (4/12) reporting social factors, (3/12) general high effort, and (2/12) favorite food items. The extraordinary situation again accumulates to almost half (5/12) the participants split between events (2/12) and restaurant visits (3/12). Three items were not mentioned after only four weeks of intervention. On the negative side, participants start to feel helpless when trying to reach healthy nutrition (3/12). On the positive side, participants start reporting knowledge gain (1/12) and a permanent reduction of food intake (2/12).

Table 33: Qualitative evaluation of user's interaction with the *Nutrilize* system - Part 1.

							Tell us how you mostly used *Nutrilize*											Tell us which functions influenced your diet							Tell us about difficulties with *Nutrilize*																				
Codes	Group	Tracking	Visualization	Recommendations	Active Days	Last Day	AfterMeal	HomeScreen	Tracking	InTheEvening	InformAboutFoodItems	MoreInBeginning	AddLaterOn	Calories	Statistics	BeforeMeal	IfTime	FeedbackHomeScreen	PlanningNutrientInfos	DecisionCalories	DecisionRecommendations	FeedbackDiary	FeedbackFoodItems	FeedbackStatistics	FoodItemsNotFound	TrackingEffort	TooSlow	ErrorsAndCrashes	RecommendationIllogical	Internet	Logout	SportCaloriesNotUnderstood	NutrientsNotFound	RecommendationPortionsIllogical	SportItemsNotFound	BarcodeScanning	ChangePassword	LearnPortionSizes	NegativeNutritionWhenLittleInput	NutritionFeedbackNotUnderstood	NutritionVeryNegative	PersonalizationNotUnderstood	RecipesNotFound	ScreenTooSmall	WeightTrackingNotFound
35	I	0.74	0.23	0.02	47	102	●	●	●		●	●							●						●	●			●							●									●
35	I	0.59	0.38	0.02	127	201			●	●					●			●						●	●			●	●																
32	I	0.73	0.24	0.02	108	139	●				●							●			●					●	●	●		●										●					
28	I	0.91	0.05	0.03	28	72		●		●						●		●			●					●	●	●		●				●											
50	Q	0.87	0.1	0.03	45	60			●	●			●						●						●	●	●		●			●		●	●										
44	Q	0.77	0.22	0	60	63	●	●							●			●							●	●		●			●		●												
40	Q	0.84	0.12	0.01	19	114			●			●	●									●			●	●	●			●															
31	Q	0.82	0.14	0.02	30	49	●					●						●							●	●					●						●		●						
35	Q	0.81	0.16	0.02	64	76	●	●					●	●									●		●	●	●					●													
31	Q	0.82	0.16	0.01	62	66									●		●								●																				
57	CQ	0.88	0.12	0	57	58	●	●	●	●				●						●					●	●	●	●	●				●					●				●	●	●	
42	CQ	0.93	0.06	0	21	67				●	●							●							●						●				●						●				
44	CQ	0.94	0.05	0	41	73	●	●	●		●	●		●					●	●					●		●	●				●													

Table 34: Qualitative evaluation of user's interaction with the *Nutrilize* system - Part 2.

Codes	Group	Tracking	Visualization	Recommendations	Active Days	Last Day	Understood	HelpfulFeedback	Appealing	HelpfulFoodItems	HelpfulInfos	HomeScreen	Demotivating	WhatIf	Confused	NotFitting	StrangeRecipes	NotCooked	ExternalCircumstances	InspiredCooking	NoDiversity	NotUnderstood	Cooked	Fitting	TechnicalProblems	WrongPortionSizes	NotAppealing	LessInput	LessTime	Habit	EaseOfUse	LessFeedback	NewContent	MoreTime	NewGoals	Timing
							Tell us about your usage of the visualizations									Tell us about your usage of the recommendations												Tell us about changes in your interaction with *Nutrilize*								
35	I	0.74	0.23	0.02	47	102	●	●				●		●		●	●			●		●														
35	I	0.59	0.38	0.02	127	201	●	●	●	●		●				●	●		●																	
32	I	0.73	0.24	0.02	108	139					●			●	●	●				●	●		●		●											
28	I	0.91	0.05	0.03	28	72																		●		●										
50	Q	0.87	0.1	0.03	45	60	●	●				●	●			●	●		●			●	●			●				●						
44	Q	0.77	0.22	0	60	63	●		●				●				●		●											●	●		●			
40	Q	0.84	0.12	0.01	19	114	●											●	●									●	●			●				
31	Q	0.82	0.14	0.02	30	49	●			●						●		●									●									
35	Q	0.81	0.16	0.02	64	76	●	●		●								●						●						●						
31	Q	0.82	0.16	0.01	62	66	●	●		●	●						●			●								●	●							
57	CQ	0.88	0.12	0	57	58	●	●	●							●	●	●			●				●			●	●							●
42	CQ	0.93	0.06	0	21	67	●		●		●							●										●			●	●	●	●	●	
44	CQ	0.94	0.05	0	41	73	●		●	●										●	●	●						●	●							

Table 35: Qualitative evaluation of user's perception of the *Nutrilize* System.

Tell us about previous experience with nutrition apps

Codes	Group	NotUse	Manually	OtherApp	SearchedFor	Internet	TooLittleTime
35	I		●			●	
35	I			●			
32	I						
28	I				●		
50	Q		●				
44	Q		●				
40	Q			●	●		
31	Q			●			●
35	Q	●					
31	Q	●			●		
57	CQ	●					
42	CQ	●					
44	CQ		●				

Tell us about (dis)advantages of *Nutrilize* compared to other apps

Codes	Group	HavingDetailledTracking	HavingNutrientOptimization	EqualTracking	HavingSportsTracking	HavingStatistics	MissingBarcodeScanning	MissingNutrientFoodItemRecommendation	MissingWeightTracking	HavingRecipeRecommendation	MissingDesign	MissingPhysicalActivity
35	I											
35	I	●				●		●				
32	I											
28	I			●								
50	Q		●		●	●			●			●
44	Q	●					●	●				
40	Q				●						●	
31	Q		●	●					●	●		
35	Q											
31	Q											
57	CQ						●					
42	CQ											
44	CQ	●	●									

Tell us how you would like to continue using *Nutrilize*

Codes	Group	TooSlow	MoreContent	OwnRecipes	WouldLikeTo	LessFrequent	CostFree	NotAlways	NotUse	OnlyIfImproved	BarcodeScanning	BetterRecommendations	Defaults	EasierTracking	InformationOnMealLevel	TooLittlePressure	TooMuchDetail
35	I																
35	I				●												
32	I								●								
28	I						●									●	
50	Q	●		●		●				●							
44	Q	●		●			●			●	●						
40	Q								●				●				
31	Q		●		●			●									
35	Q				●												
31	Q	●	●			●											
57	CQ	●				●						●		●	●		
42	CQ		●	●	●												●
44	CQ		●	●													

Tell us how you would replace Nutzilize

Codes	Group	NoApp	OtherApp	NutritionFeedback	OtherInfos	OtherMotivation	OtherTracking	SportsTracking
35	I							
35	I							
32	I							
28	I							
50	Q		●					●
44	Q	●			●			
40	Q	●						
31	Q							
35	Q	●						
31	Q		●	●				
57	CQ	●	●					
42	CQ					●	●	
44	CQ		●					

Table 33 (block 1-3) and table 34 (block 4-6) show a summary of the users interaction patterns and the interview data on their usage of the system. The first block inquired about the way different participants used *Nutrilize*. The second block asked which features of the application the participants felt had influenced their diet most, while the third block asks about difficulties with the application. Afterward, the participants were interviewed in more detail on their usage of the visualizations (block four) and the recommendations (block five). Finally, we asked the participants what they changed in their interactions towards the end of the study (block six). There are three different aspects reported when asking after the usage of the application in block one. First, the timing of the usage, second, features of the application, and third, changes in interaction. Regarding the interaction timing, the participants are mostly split between entering their meals directly after the consumption (7/13) and entering everything in the evening (5/13). Only (1/13) participant reports entering the food before the meal starts. Additionally, (3/13) participants report having to add things later on several occasions. Regarding the features, both the tracking (6/13) and the home screen (6/13) are commonly used. Other important features that are mentioned by multiple participants are the calorie history (3/13), the food item information (4/13), and the nutrient history/statistical view (3/13). Finally, regarding changes in interaction, (4/13) participants reported having reduced the amount of time they spend with the application after a while, and (1/13) having switched to manual prerecording and later tracking of the food. The second block asks the participants which features they used and how it influenced their diet. Most of the participants used the features for feedback on their past nutrition. The majority (7/12) did this using the home screen while other individual responses went to food details (1/12), statistical nutrient history (1/12), and the diary (1/12). Another part of the participants used the application to decide on the next meals with both the recommendations (2/12) and the calorie overview (2/12). Finally, three participants (3/12) used the application for longer-term planning by looking into the nutrient description and the suggested food items for each nutrient. The third block asked participants about their difficulties with the application. Almost all participants had problems finding food items within the BLS database (11/13), and many (9/13) complained about the effort of tracking their diet. Regarding the technical aspects, most criticized the speed of the application (7/13), about half of the participants mentioned having received error messages (6/13), and some reported problems due to low internet connectivity (3/13) or having to log in again (3/13). Another aspect that was criticized is that the recommended meals (4/13) and the recommended portion size of these recommendations (2/13) seemed unlogical or untrustworthy to the participants. Another type of problem was the lack of understanding of the application. (3/13) participants did not understand how the calories were adapted after physical activity. Others did not understand the nutrient feedback they received (1/13), how the systems were personalized (1/13), why their nutrition was so negative (1/13), and why the nutrition was worse when they stopped tracking (1/13). A different problem that participants had was not finding the features the app was offering, such as the nutrient details (2/13), the sports diary (2/13), the weight history (1/13), and the recipe instructions (1/13). Finally, individual problems were reported, such as portion estimation (1/13), missing a barcode scanner (1/13), login after having changed the password (1/13), and too small screen size (1/13). The fourth block asked about the perception and usage of the different visualizations in the application. Almost all participants (11/12) state they have understood the visualization's content, and almost half of the participants (5/12) state that they are appealing. The participants report the visualization being helpful as feedback (6/12), to choose food items (5/12), and to get detailed information (3/12). (3/12) participants put special focus on the home screen as an important tool, while (2/12) thought it to be demotivating. (2/12) participants mention the "What-If" visualizations within the recipes and food items. Finally, (1/12) participants thought the visual feedback was confusing and did not understand the metaphors' meaning. The fifth block asked about the perception and usage of the recommendations features. Only part of the participants used the recommendations either as inspiration (4/13), as a fitting suggestion (2/13), or as a literal guideline (2/13). The reasons for not using the recommendations (5/13) varied. A number of participants thought the recipes were strange (6/12), while others said they did not meet their preferences (6/13), they were too repetitive (3/13), or they had wrong portion sizes (2/13). Others explained why they could not use the recipes because of external circumstances (4/13) or lack of understanding (3/13). Finally, (2/13) report technical issues, and (1/13) states missing appeal of the recommendations. Finally, the sixth block asked participants if there were any changes in their interactions between the two interviews. Most participants state reducing tracking (5/8), the time for the application in general (4/8), or the retrieval of feedback (2/8). On the other hand, a number of participants report having established their interaction habits (3/8), finding new features (2/8), regarding the interactions as easier (2/8), spending more time in the application (1/8), setting new goals (1/8), and changing the timing of the interactions (1/8).

Table 35 shows the interview data on the general application perception in comparison to previously used or prospect systems. The first block focusses on which applications the users have previously used. Most of the participants have not used an application for nutrition before (8/12) since they either have not used any tracking prior to the study (4/12) or have tracked manually (4/12). Three participants have searched for an application but not found a fitting one yet (3/12). Three participants mention apps they have been using (3/12), namely MyFitnessPal, MyCalorieApp, and an unnamed insurance application. (1/12) person mentions searching the internet for nutrition information and (1/12) mentions stopping the app usage due to lack of time. The second block focusses on the pros and cons of *Nutrilize* compared to other applications. This question was only answered by participants that have a comparison to other applications (8/13). The most frequent pros are the detailed tracking functionality (3/8) and nutrient optimality feedback (3/8). The second most frequent pros are tracking physical activity (2/8) and the statistics overview (2/8). Only (1/8) mentions the recipe recommendations as a pro argument of the *Nutrilize* application. (2/8) participants mention that the tracking is equivalent to other applications. On the negative side, the most frequent cons are missing barcode scanning (2/8), missing general recommendations of food items for nutrients (2/8), and missing weight tracking (2/8). The weight tracking visualization was part of the system but was seemingly not discovered. Further cons mentioned are missing a nice design (1/8) and missing features on physical activity (1/8). The third block focusses on whether and how the *Nutrilize* application would be used in the future. (4/12) participants state they would like to use *Nutrilize* in the future. A number of participants stated they would use *Nutrilize* but less frequently (3/12) or not always (2/12). (2/12) participants would not use *Nutrilize* in the future. Other participants have further conditions to their usage, such as *Nutrilize* free of cost (3/12), and improved (2/12). The most important improvements mentioned are faster performance (5/12), more content (4/12), and adding own recipes (4/12). Other features that are mentioned are better recommendations (1/12), information about each meal (1/12), easier tracking (1/12), default settings (1/12), fewer details (1/12), and more pressure (1/12). The fourth block focusses on applications that might replace *Nutrilize* after the end of the study. Since this question is part of the final interview, it was only answered by (8/13) participants. There are an equal number of people not wanting to use any application in the future (4/8) and wanting to use or search another application (4/8) with (1/4) participant having stated both. Of the four participants wanting to use another application, (2/8) have a target (MyFitnessPal and Balance), while (2/8) first want to search and test applications. The needs mentioned in connection with future application usage are getting nutrition feedback (1/8) and tracking physical activity. The needs mentioned to be important beyond the usage of an application are getting motivation (1/8), searching for nutrition information (1/8), and tracking diet (1/8).

10.4 DISCUSSION OF RESULTS

Studies suggest that personalized recommendations improve the outcome of nutrition interventions (Celis-Morales et al., 2016) that mobile applications facilitate bringing such personalized feedback into the daily lives of users (Flaherty et al., 2018). Our study offers insights into the long-term effects and limitations of *Nutrilize* as an example of such a personalized nutrition assistance system, by taking standardized pre- and post-measurements, tracking the interactions with the system, and interviewing the participants about their experience with the system.

10.4.1 *Review of Research Questions*

In this study, we asked the question "How does long-term usage of a nutrition assistance system influence

- The physique of the user,
- The nutrition behavior of the user,
- The interaction with the system, and
- The perception of the system?".

Concerning the physique, the study results indicate changes in BMI, but they are not significant. For the WHR, changes are almost not visible. The missing significance of both values could be due to the small sample size or to the duration of 2-3 months, which is still relatively low compared to traditional interventions of at least six months to multiple years of follow-up. Simultaneously, there is also only little change in calorie intake, with the intervention group showing the most substantial changes. One reason for this might be that the application is not per se enforcing weight loss, but focusses feedback on the nutrient intake. While optimizing fat or sugar intake can lead to calorie intake changes and weight loss, participants who focus instead on vitamins might not lose any weight. There are almost no physical activity changes either, which are measures with the PAL and Baecke metrics. The same explanation holds that while exercise tracking was supported and burned calories were visualized, additional activity was not advertised or required.

Concerning the questions of how our application improved nutrition behavior, we focus on two aspects - calorie intake and nutritional ability. We show that the calorie intake is decreasing between the pre-test and the post-test measurement with a FFQ questionnaire. However, a closer look into the daily calorie intake reveals that the daily calorie intake has strong fluctuations over time. While there is a trend visible towards lower calorie intake, this trend could also be caused by participants' selection still actively tracking their dietary intake. As we see in the interaction analysis, tracking activities suffer from large dropouts. In literature, this phenomenon is also called the winner's or survivor's bias (Mateo et al., 2015, Wu et al., 2009). It indicates that only participants for which the intervention is most effective or motivated participants remain active and engaged until the later phases of a study. Thus measures towards the end of our study might represent a different sample than at the beginning, which causes our measured effects. Another factor that puts our results of calorie intake changes to question is the difference in calories tracked with the FFQ and the application diary. Since nutritional and caloric content is usually underestimated (Thompson and Subar, 2017), the FFQ measure seems to be the more reliable source, which in turn could imply, that the fluctuations and trends visible in the daily tracking are actually due to the effort of monitoring, which was also mentioned by participants in the interviews. One positive aspect of this dilemma is that the nutritional ability is less sensitive to these fluctuations and even to the difference between FFQ data and diary data. Besides biasing our overall outcome analysis, the daily underestimation is propagating to other system variables, as shown in our visual measurement analysis. For example, we see more nutrients with optimal intake for those entries with more tracked calories. This improved nutrient coverage might be due to such entries being less underestimated and providing a more realistic intake representation. Such biasing variables are thus integrated into our multilevel regression model to differentiate between their side-effect and the main intervention effects. This regression analysis showed that the optimal nutrient intake is not influenced by the time passed in the first 12 days, but it is influenced by time in the full 2-3 month sample. The effect of dropout is further counteracted by using the user as a random intercept in the model and thus not mixing effects between participants. In summary, this model shows that the application improved optimal nutrient intake in the long-term.

Concerning the interactions with the system, we see that the intake tracking takes up most of the time participants spend with the system. While the participants provided negative feedback about the high effort caused by tracking, it was also a significant positive influence on the optimal nutrient intake. Of course, this impact is twofold. More tracking leads to more dietary information and less underestimation, which could cause the optimal intake. However, we did include the calories tracked on a specific day as another effect in the model to discriminate these two effects. Thus, tracking is an effective feature for optimal nutritional behavior. The other danger od this high effort in tracking is the dropout that might be caused by it. We observed that the number of interactions with the system decreased quickly and was at about half of the initial volume after three weeks and a quarter of it after eight weeks. The final four weeks were one subset of the study procedure and are thus biased. However, of the initial 11 participants in that branch, four still used the application on day 90. One of the reasons named for dropout was the effort of using the application. This effort mostly refers to the tracking since all other features only work reasonably when sufficient intake tracking was provided. Other reasons stated during the interview are discussed below. The second most effective feature set is visualization feedback, and especially the statistics screen and the home screen. The statistics screen was used more consistently over time and even when other features were already facing dropout. This screen might be relevant even in the later stages of the study because it provides better insights with increasing time. After using the application for weeks, the immediate feedback might seem repetitive and already known. In contrast, historic feedback can, for the first time, conclusively reveal trends and changes in behavior. Overall the usage of features was subject to differentiated dropout patterns and higher fluctuations between days. The administrative features, for example, were mainly used at the beginning of the study. They further harm the optimal nutrient intake, which might be due to events later in the study, where administrative features needed to be used due to errors in the system. This assumption becomes especially apparent when drilling down to individual screens and observing the login screen as one of the most negative influences. This screen should not be used later in the study except for crashed or internet connectivity issues. Such an interpretation is further in line with the feedback given during the interviews that some participants had usability issues with the application, especially when facing low internet connectivity. Other features, such as the recommendations or the calorie overview, were used at a consistently small scale. Comparing the effects during the first 12 days with the effect of recommendations in the short term study showed that recommendations seem to be less effective in the long-term study. One reason for this drop might be the difference in the recipes provided. In the short-term case, the recipe database was smaller but based on a popular recipe magazine. In the long-term study, due to copyright reasons, recipes from the open-source KochWiki (Koch-Wiki, 2019) were used. These recipes represent more basic meals that might be less attractive. In the full long term study models, the recommendations are no significant influence on optimal nutritional intake. One final point of discussion is that the most influential features align with the most used features. This correlation might be an issue of the statistical analysis. However, the preferences retrieved from participants also align with these screens as the most desirable features, so their effect is likely real. In summary, this model shows that visual feedback and tracking are the most relevant features for optimal intake, and the recommendations need to be significantly improved before being effective. Some of these improvements are discussed during the interviews.

We analyzed multiple questionnaires and in-depth interviews concerning the system's perception and its integration into the participants' daily lives. As mentioned, the recommendation feature needs to be significantly improved to be effective. Within the questionnaires, we could only derive that the effort of following these recommendations is high, and the perceived health and taste personalization is low. However, during the in-depth interview, we could drill down into the issues of using these recommendations in real life. Some participants reported only using the recipes as an inspiration to derive new changes in their diet, such as eating more fruit, when many fruity breakfast recipes were suggested. They explained this with the lack of availability of all the ingredients at the time of the decision. They further describe the recipe recommendations as strange with some recipes not being perceived as healthy and thus being mistrusted. Finally, they did not feel their preferences represented in the recommendations. This lack in preference representation might be due to the high emphasis (75%) on health utility. Features that were perceived more useful are the tracking features and visual features. The tracking was conducted directly after the meal or in the evening for all daily meals depending on the user's preference and external restrictions such as access to the device or internet connectivity. While the visual feedback was liked, perceived as helpful, and appealing in the surveys, the interviews helped us drill down to each feature's actual impact Users reported using the home screen to receive feedback on their performance and to motivate themselves. The further reported consulting the calorie overview of the recommendations in case of immediate decisions. Finally, they used the nutrient details and specify the list of food items for a certain nutrient for long term planning of dietary changes such as eating an apple each day. This distinction should lead the future design of applications to, e.g., personalize and adapt the food items suggested for each nutrient, or to make the recommendation overview more accessible for in the moment decisions, such as recommending single items or substitutes. Over time the participants changed their interactions with the system. They report spending less time and especially less tracking efforts, which is in line with the logging of interactions. In the future, they would either use the system only occasionally or not at all. If they used it, they would further require improvements to the tracking effort, such as creating their own recipes, scanning barcodes, and adding common food items. This wish for less tracking corresponds to the user's decrease in interactivity in this area. Given this background, it is further likely that the decrease in feature usage might be caused by their decreased functionality without the tracked information instead of due to a loss of interest. Such changes in perception and action over time are further reflected in the SUS score of 59, which is improved from the first prototype analyzed in the 21-day pilot study in chapter 8 with a SUS score of 52. However, both scores are way below the scores of 65 and 76 achieved in the initial usability test. Compared to this, Ferrara et al. (Ferrara et al., 2019) report SUS scores of commercial applications between 46.7 for MyDietCoach and 89.2 for LifeSum. The above reasoning about long-term usage might explain this drop in interest and heightened awareness of issues and challenges. Besides the interactions, the nutrition of participants changed over time, as shown in the previous section on our system's effectiveness regarding optimal nutrient intake. During the final surveys, participants reported on changing vegetable, fruit, and sugar intake, as well as portion sizes. Beyond the survey, the participants positively reported not feeling constrained by these changes in their everyday life. They also explained that their strategy for these changes is based on the substitution or addition of individual food items instead of focusing on specific nutrients. This could indicate that substitute based feedback would be a more natural way to support participants in their changes. Towards the end of the study, participants even positively reported that their change increased their awareness and enjoyment of eating as well as their knowledge of nutrition in general and their own nutrition in particular. On the other hand, they were aware of and disappointed by the lack of physical changes, which can be confirmed by the measurements. One participant summarized this trade-off in application focus nicely by stating that in the beginning, the lack of weight loss demotivated her, but later on, her increased feeling of wellbeing shifted her internal goal-setting. Finally, all the changes in nutrition were subject to relapses and struggles. Most prominently, participants reported exceptional events, favorite food items, social situations, and tracking effort to impede their change maintenance. While these external forces can not be avoided in everyday life, future applications could detect these contexts and provide context-aware psychological support strategies. In summary, the in-depth interviews explained some of the observed measurements in more detail and provided suggestions for future improvements. Many of the reported issues lead back to a higher need for personalization and context awareness, as suggested by previous work (Rokicki et al., 2016,Kusmierczyk et al., 2015).

10.4.2 *Study Limitations*

The *Nutrilize* application has constraints regarding usability and feature availability. First, our aim at high precision nutritional content has lead to using the BLS as a food item database. The BLS database has to lead to issues with non-layman terms and thus low searchability for certain food items. Furthermore, the restriction to open source data has led to integrating recipes from the KochWiki database, which covers many basic recipes, but not as many "currently popular" recipes. In the effect analysis, we also see that the underestimation in daily tracking is propagating errors to the feedback users are receiving. We try to correct for this in our models by including the daily calorie count. Finally, the study we conducted only had a limited number of participants from a restricted area around Munich and is thus biasing the results. Finally, while the study's duration is uniquely long for mobile applications, it is still relatively short compared to traditional interventions. We considered these restrictions in our analysis and interpretation of results and believe that the derived conclusions will transfer to future nutrition assistance systems.

10.4.3 *Implications for Future Systems*

The study reveals successes in influencing the participants' nutrition behavior but shows that future systems need to reduce the tracking effort by automated methods and default predictions to have a higher impact and more prolonged engagement. One way to do so is picture-based tracking. However, a more precise and simpler remedy might be to improve the BLS database to provide everyday synonyms and likely representatives for common commercial products. Further, future systems need to include contextual information, such as the canteen menu, the fridge content, the available time, or the children's preferences. Some solutions, such as intelligent kitchenware, are already being researched. Other suitable solutions might be substitute based recommendations and group recommendations. Finally, personalized recommendations were often mistrusted when they went against everyday population-based advice. Thus, there is more need for explanations and guidance when using such complex advice systems. This feedback falls into place with the upcoming research area of explainable artificial intelligence.

10.5 CONCLUSION

In this chapter, we contribute a long-term study of the usage of our nutrition assistance system *Nutrilize*. We investigated the physique changes, the behavior changes, the system interaction, and the users' experience for 34 participants (11 control, 11 3-month, 17 2-month). The *Nutrilize* system provided dietary tracking, prospective, retrospective, and perspective visual feedback and personalized recipe recommendations. Our results suggest that the system effectively changes behavior, but struggles with high dropout due to different contextual factors. In summary, our contribution shows the promise of nutritional assistance systems for providing daily support in making healthy decisions. This study's findings can improve the design of future applications and study settings, as discussed in 10.4.3.

This chapter concludes the second part of this thesis focussing on socio-technical systems for healthy nutrition in adults. This final relevance cycle shows such systems' potential and critical insights into the limitations in real-life settings. While there is no significant change in the participants' physique, we observe that the nutritional ability is positively influenced by the time spent in the study. We confirm the caloric difference between FFQ-based and diary-based intake assessment observed in the pilot study (chapter 8)), but see a smaller distinction in the nutritional ability derived from both measures. Both the interaction amount, the feature impact on optimal nutritional intake, and the perception questionnaires indicate a strong preference for visual feedback over the other features offered in the application. This study's main limitation is that we observe a strong dropout over time, which might bias our results. Causes for such dropout are derived from our in-depth interviews to be mainly social situations, exceptional events, time-pressure, and favorite food items. Beyond the scope of this thesis, the *Nutrilize* system should be evaluated in a one-year-long study. Further, the system should be extended by the designed social platform for recipe sharing and diet rating, which was instead investigated in the separate *Appetite* system outside of this thesis. Finally, the dietary tracking while showing a large positive impact on behavior change is also the most time-consuming and criticized feature of the application. In the future, photo-based alternatives with either automated analysis or user-based ratings, as suggested for *Appetite*, should be considered in more detail.

Part IV

DISCUSSION AND CONCLUSION

11

REVIEW OF RESEARCH QUESTIONS

Since our research methodology rests on the usage of specifically designed artifacts, all contributions are on level 1 of the classification given by Gregor and Hevner (Gregor and Hevner, 2013). This section reviews the results and lessons learned in the previous rigor, design, and relevance cycles and sets them into perspective to one another.
In this thesis, we focus on different ways in which socio-technical systems can support healthy food choices. To address this problem, we follow the design science methodology to evaluate design artifacts regarding four research questions:

RQ 1: How can socio-technical systems support nutritional knowledge?
RQ 2: How can socio-technical systems support nutritional motivation?
RQ 3: How can socio-technical systems support nutritional behavior?
RQ 4: What are the limitations of socio-technical systems in real-life contexts?

In the following sections, we will summarize the results from all chapters in both parts of the thesis regarding each of these research questions.

11.1 R1: NUTRITIONAL KNOWLEDGE

Socio-technical systems can target the improvement of different types of knowledge. Traditional population-based interventions target the population's explicit knowledge of rules, tasks, or metrics about improved behavior, e.g., the ten rules of the DGE, or lists of healthy food items, which in turn lead to conscious behavior changes. Applications that focus on individual behavior change don't rely on this explicit knowledge but instead target a subconscious understanding of good and bad actions or the ability to make decisions on a subconscious level. For example, if eating hamburgers leads to negative behavioral feedback, users would learn to avoid it without knowing the specific rules involved. This type of knowledge is often based on personal experiences and values and might not be generalizable to other people's diets.

In the children's case, our studies reconfirmed that serious games successfully transmit knowledge of nutrition. However, the explicit rules of the DGE were transmitted better in a teaching setting than in the gaming context. Furthermore, we see that the pressure perceived during the classical lecture impeded knowledge gain, which was not the case in the gaming scenario. We conclude that serious games are an effective and scalable solution to impacting children's subconscious knowledge of nutrition. This topic of nutrition games is further discussed in chapter 12.

In the adults' case, our studies revealed that even though the visual feedback on past and present behavior improved nutritional behavior, the participants were not aware of their knowledge and could not express their insights. While this does not impede the application's effectiveness, it does hinder exchange on the acquired knowledge with peers. The type of knowledge they obtain is subject to repeated feedback given in the application. For example, participants learn over time that one food item works well in improving their scores and try to eat more of it. Thus, the participants gained knowledge on how to improve their personal nutrition deficits. In some cases, this leads to counterproductive behavioral changes because the knowledge gained in this way is too specific and does not consider more complex interdependencies. Such overfitting can be mitigated by empowerment through explanations. In the case of our personalized recommender system, such explanations were perceived very well. Participants remembered repeated suggestions (e.g., fruit es recommended for breakfast on most days), and abstracted this feedback into a guideline for future behavior. We conclude that the implicit knowledge gained in behavioral interventions should be accompanied by explicit knowledge to empower the users in their change process.

Socio-technical systems can improve subconscious nutrition knowledge by serious games or by providing repeated behavioral feedback. Explicit knowledge is harder to transfer and might rely on active reflection via explanations or social exchange.

11.2 R2: NUTRITIONAL MOTIVATION

One way to measure the motivation towards a specific behavior is to survey the attitude, efficacy, and intention based on Ajzen's theory of planned behavior (Ajzen, 2002). Another way to measure motivation in the form of determination is by observing the daily engagement and dropout of users in the socio-technical system. Finally, general motivation can be retrieved as a subjective self-assessment.

In the children's case, we see slight motivation changes, especially in the attitude component after applying gamified feedback. We further see that these changes depend on personal variables (age, gender, BMI, personality, knowledge, behavior), and contextual factors (success during the intervention, perception of the intervention). The perceived competence gave the most prominent impact during the gaming experience in both the physical activity game and the healthy nutrition game. In the case of the serious game for nutrition, the attitude change was supported this perceived competence. On the other hand, the change in intention was dependent on both this change in attitude and the perceived enjoyment of the gaming experience. Unfortunately, enjoyment and success, which partially relates to perceived competence, were negatively correlated, leading to contradicting effects. We conclude that perceived competence and enjoyment are crucial factors in the effectiveness of game interventions, and serious games thus need to be tailored in their difficulty to individual users. This topic of personalization is further discussed in chapter 12.

In the adults' case, we received negative feedback about dietary tracking with participants reporting it to cause frustration and thus demotivation. We further received feedback that the visualizations are helpful and motivating for many participants, while they can be demotivating to users when repeatedly showing the same errors. Concerning the engagement, we see a reduction of system interactions to about half of the initial measurements after two to three weeks. We further see that visual feedback is the most reliably used feature, even after many other screens are already less visited. We conclude that positive visual feedback components are an effective measure to change dietary behavior and increase long-term engagement. We further see a need to reduce the frustration and dropout caused by dietary tracking. This topic of tracking is further discussed in chapter 12.

Socio-technical systems can improve motivation for healthy nutrition by tailored serious games or by providing positive visual feedback. Tracking effort is an impeding factor that needs to be addressed in future research.

11.3 R3: NUTRITIONAL BEHAVIOR

Improvement of nutritional behavior has different perspectives. One aspect is the reduction of weight, BMI, and WHR by reducing calorie intake or increasing physical activity. Another aspect is eating healthier according to the ten rules of the DGE, e.g., eating more vegetables. Finally, the intake status of each nutrition can be evaluated using the DRI guidelines. This intake can further be evaluated relative to the difficulty of achieving optimal intake on each nutrient, e.g., protein, is straightforward to consume optimally.

In the children's case, we see a decrease in physical activity behavior in both the control group and the group with gamified personalized feedback. However, we see that the positive pre-test behavior had a lower decline when using our socio-technical system than for children without the system. For the serious nutrition game, the behavior was not assessed post-intervention, due to the short intervention time, and the strong influence of parental behavior on the participants' nutrition. With the research conducted within this thesis, we cannot provide a conclusion on the behavioral effect of serious gaming.

In the case of adults, we cannot observe significant physical changes such as BMI and WHR. However, participants report having changed their behavior by eating additional fruits, lowering portion sizes, and eating more consciously in general. We further see an improvement in nutritional behavior weighted by nutrition difficulty. We also observe that the optimal intake of nutrients is positively influenced by the intervention's duration, personalized visual feedback, and dietary tracking. Finally, we see a positive enhancement of this effect when tailoring the difficulty of advice. We conclude that socio-technical systems can improve nutritional behavior, especially with tracking, visual feedback, and personalized feedback. These topics of tracking and personalization are further discussed in chapter 12.

Socio-technical systems can improve nutritional behavior with dietary tracking and personalized visual feedback. We cannot confirm any effect for serious gaming.

11.4 R4: LIMITATIONS IN REAL-LIFE CONTEXTS

The limitations of socio-technical systems can be differentiated into the technical limitations and the user's social or personal limitations. Furthermore, the real-life contexts provide a third set of limitations that need to be discussed when considering healthy nutrition systems.

In the children's case, the major challenge is the individual perception of and response to serious games. While knowledge gets improved by most serious games for nutrition, the change in intention, and finally in behavior are highly dependent on a network of personal and experience factors. Within our studies, we extract perceived competence and perceived enjoyment as the most relevant experience factors. However, we observe that not all successful intervention indicators are positively correlated with the intended change in motivation and behavior. In our studies, in-game success impeded enjoyment and thus change in intention. Perceived competence, on the other hand, improved attitude, which is a precondition for intention changes. As discussed in the motivation research question, we conclude that serious games need to be personalized in their difficulty. In line with this observation, the focus groups reveal that games for even slightly different age groups might have to target widely different preferences and expectations. This topic of personalization is further discussed in chapter 12. Finally, dropout and losing interest are a substantial risk in the long-term, as shown by the study on gamified physical activity feedback. All participants lost their initial positive physical activity rate. We conclude that long-term experience with the application and personal fit of the application can impede intervention effectiveness. These topics of personalization and long-term maintenance of behavior change are further discussed in chapter 12.

In adults, there are technical, social, and contextual limitations to improving nutritional behavior. On the technical side, the availability of highly accurate and realistic nutrition information for food items is a considerable restriction. While the BLS database provides accurate nutritional information, it is not fit to be used in everyday contexts where participants search, e.g., for commercial snacks, or colloquial food terms. Grocery items, on the other hand, do not always or not sufficiently provide nutritional information. We conclude there is a need for a more open and standardized provision of accurate nutritional databases for commercial food items. Further, the effort of manual intake tracking is the highest source of frustration for the participants, and its declining adherence leads to system-wide error propagation. Future tracking methods could build on such improved databases with barcode scanning or improve current approaches to picture-based tracking. The topic of tracking is further discussed in chapter 12. Participants report social eating situations, extraordinary events, and favorite food items as their biggest relapse factors. We conclude that there is a further need for social or group recommender systems and context-aware guidance for extraordinary situations, e.g., by compensating the event with prior actions. Finally, on the contextual side, participants did not incorporate recommended meals in their daily plans because they did not fit their available time and food resources, mood, or general abilities and openness. We conclude that increased contextual awareness and even stronger personalization are needed in socio-technical systems providing recommendations. These topics of recommender systems and personalization are further discussed in chapter 12.

Socio-technical systems need to overcome real-life limitations by adapting to personal aspects, i.e., age and ability, contextual factors, i.e., social environment and limitations in available resources, and by avoiding frustration in long-term usage, i.e., through high effort or boredom with repetitive actions.

12

DISCUSSION AND FUTURE PROSPECTS

This chapter aims to review the lessons learned in our previous design and relevance cycles and compare them to other groups' recent research. The following sections discuss the potential and limitations of socio-technical systems for healthy nutrition discovered in this thesis by comparing them to new related work published after this thesis' research. This chapter is split into dietary tracking, nutrition games, food recommender systems, personalization for persuasion, and behavior change as the topics extracted during the research questions review. The final two sections discuss open research challenges and conclude the discussion with specific opportunities for extending this research.

12.1 DIETARY TRACKING

We conclude in chapter 11 that dietary tracking is a strong influence factor on improving dietary behavior, and, at the same time, a source of errors that propagate to other features and a source of frustration and dropout due to technical limitations. We propose image-based tracking as a low effort alternative. This solution would significantly reduce the burden of tracking and the resulting frustration of users while still providing the impact on nutritional behavior due to the increased awareness of personal intake. The crucial point why such techniques were not adopted in this thesis is the error rates present in even the most advanced image recognition approaches. For example, Sahoo et al. (Sahoo et al., 2019) recently published their food image recognition approach. While they show a good top-5 accuracy, they only reach 83.2% of top-1 accuracy and further acknowledge issued with new food classes and the estimation of calories from images. Such automated approaches are promising but not accurate enough to be used in socio-technical systems for healthy nutrition, as confirmed by a recent survey on AI for nutrition recommender systems (Theodoridis et al., 2019). We argue, however, that we observed other error rates of similar impact in our studies. While the BLS provides highly accurate nutrient information, its potential was not used due to the user's struggle with identifying the correct items to be tracked. Additionally, the daily tracking revealed higher underreporting in terms of calories than the FFQ method, which is estimated to have 11-35% error in this category (Thompson and Subar, 2017). Since the error rate is that high, even with accurate databases, our picture-based rating methods, as proposed in chapter 7.8 with errors of 10-28%, would also be competitive. However, a discrepancy between accuracy in macro- and micro-nutrients, as shown for commercial applications (Ferrara et al., 2019), should also be expected for such rating-based estimation.

We conclude in chapter 11 that nutrition games are effective in transferring knowledge and partially effective in imparting motivation when calibrated to the user's abilities and preferences. Our results are in line with a study by Long et al. (Long and Aleven, 2017), which compares an educational game with an intelligent tutoring system (ITS). While the students enjoyed the game more, they learned more when using the ITS. We further observe that both the gaming and the teaching interventions lead to slight changes in attitude, efficacy, and intention, dependent on gender and other personality traits. A recent analysis of 14 serious games for eating (Kohli and Chadha, 2018), confirms these observations by showing potential for increasing attitude, efficacy, intention, and even behavior when playing the surveyed games. While this survey focusses on positive main effects, other recent work (Schmidt-Kraepelin et al., 2019) warns against negative side effects of using gamification for health behavior, namely undermining intrinsic motivation, motivation decreasing over time, unfulfilled expectations, a distraction from health purpose, trivializing the health context, reduced usability, cheating the self, rewarding incorrect execution, overuse, cheating others, overemphasized peer pressure, exaggerated punishment, feeling of manipulation, discouragement due to failure, privacy infringements, fostering behavior that harms third parties. In our studies, we see part of these side-effects confirmed. For example, the negative correlation between game success as a representative of ingame knowledge and perceived enjoyment could be a case of distraction from health purposes. Similarly, we see more negative feedback on the system than in the focus groups, which could be an example of motivation decreasing over time. Finally, we observe a negative correlation between perceived pressure and knowledge gain, which could represent a discouragement due to failure. The best example of a comparable recent serious game for healthy nutrition is the kids obesity prevention program (Mack et al., 2019). While covering a broader scope of knowledge than the *Fit Food Fun* game, they have surprisingly similar game concepts, such as a backpack game to teach energy balance, a representation of food groups by animals (in FFF by colors), a racing game supported by different food items, a game on sugar content, and the comparison between energy intake and physical activity. The results are also in line with the *Fit Food Fun* results with a significant knowledge increase and no apparent change in behavior. Considering our results and their alignment with more recent studies, we see a strong need for systematic analysis of the interactions between mediating factors, game features, and targeted outcomes. We strongly propose further studies that conduct Structural Equation Modelling (SEM) or BBN to extract the pathways between these measurements in long-term interactions with serious games. Otherwise, serious games for health behavior might be without main effects and even trigger negative effects. We expect that these pathways will be similar between different targeted health behaviors based on our physical activity and nutrition game studies.

We conclude in chapter 11 that food recommender systems need to be significantly improved. We propose five central extensions of food recommender systems, namely diversity over time, extended standardized datasets, contextual awareness, group recommendations, and trust enhancing justifications. Recent work on food recommender systems already started addressing some of these proposed aspects. Regarding the diversity, (Toledo et al., 2019) built an extensive recommender system for menus and daily meal plans. In addition to food profiles, user profiles, nutritional history/context, and preference based on history frequency, which are similar to the *Nutrilize* approach, the authors include the frequency of recently consumed/recommended items to diversify the recommended items. Toledo et al. also address the additional proposition of trust enhancing justification by providing a visual interface to explain the recommendations done in text form in *Nutrilize*. The combination of solving the need for trust with visual feedback seems promising according to the positive feedback on our studies' visual features. Unfortunately, the authors did not evaluate their system on real users yet, so comparing their results is not feasible. Regarding the foundation in standardized databases, we know of no recent work solving this issue. Ideally, laws requiring detailed nutritional information labeling would address this lack of information on commercial products. For better information on recipe data, natural language processing of recipe steps to detect ingredients' processing state is a promising approach. However, already a simple embedding of nutritional databases during the recipe creation would immensely improve nutritional information on recipes. Once such preconditions are fulfilled, recommender systems could simply suggest healthier alternatives to currently selected recipes. One such approach was conducted by Chen et al. (Chen et al., 2019) in their NutRec system. The authors show how their algorithm can improve the health value or recommended recipes according to the WHO score while keeping the ingredient requirements provided by the user. Another form of such substitution that addresses single ingredients could further improve the contextual fit issues that we propose to improve. Such an approach has recently been promoted by Haussmann et al. (Haussmann et al., 2019) in their food knowledge graph. The FoodKG offers a systematic way to extract multidimensional food attributes and thus to find similar alternatives with better nutritional values. FoodKG can further easily include user-specific constraints, such as allergies and intolerances, situation based constraints, such as the availability of ingredients, and mood/context-based constraints, such as fast cooking. Again, no real-life studies have been conducted yet and thus cannot be compared. The general lack in the maturity of food recommender systems that we observe in our studies is further confirmed by an analysis of Min et al. (Min et al., 2019). This analysis states that food recommendations are still in their infancy with open challenges remaining for multi-sensor integration, personal models including food preference learning, visual food analysis, knowledge graphs combined with deep leaning on large benchmark datasets, and explainability of multi-modality food recommendations. We strongly encourage the community to advance the implementation of personalized food recommendations, because we see a great potential of this technology to provide in-time decision support as reported by our study participants.

12.4 Personalization for Persuasion

We conclude in chapter 11 that personalization is essential to improving knowledge gain, motivation gain, and behavior change. We propose further research on tailoring both serious games and persuasive systems to the user's personal abilities, preferences, and current context. Several recent publications confirm this need for improvement. From a theoretical point of view, Erdbrink et al. (Erdbrink et al., 2019) discuss scenarios in which the given context can change the reaction to the four persuasive game design principles self-monitoring, suggestion, competition, and comparison. The authors indicate that depending on the context, e.g., repetition, and sentiment of feedback, motivation, and ability can either be enhanced or reduced by each of these principles. The authors further conclude that competition and comparison are riskier concerning their context and more powerful when adapted appropriately. This risk is in line with two observations from the *Fit Food Fun* study where perceived pressure inhibited the learning effect, and success in gaming was negatively correlated with enjoyment and perceived usefulness. In contrast to the authors, we see an important potential not in exchanging competition with collaboration, but instead with tailoring the competition difficulty to the user's abilities. Such an approach could be achieved by matching the social communities within a gaming environment. Other studies have investigated single correlations of mediators with persuasiveness. For example, Orji et al. (Orji et al., 2019) show that using a single fitting persuasive strategy is more effective on the respective user than implementing a broad arrangement of strategies. The authors further show guidelines for providing a good strategy for many users by implementing tailored visualizations. This focus on visual persuasion is in line with many *Nutrilize* users preferring the visual feedback over other features in terms of usefulness and likability. Another publication by Oyibo et al. (Oyibo and Vassileva, 2019) investigates the influence of culture on the susceptibility to persuasion. The authors show that individualist users are more likely to be susceptible to personal features (goal-setting/self-monitoring and reward) than to social features (cooperation and social learning). This preference is again in line with most users preferring the personal nutrition visualizations as a feature of *Nutrilize* and participants preferring the Rasch-based personalization of visual feedback. Finally, one main challenge is quantitatively modeling the user. Recent research shows the first approaches to do this automatically by deriving the Big-Five personality traits from patterns in smartphone usage (Stachl et al., 2019). According to both our studies and these recent publications, we propose to focus further research on tailoring socio-technical systems to ability. For serious games, this could be done by both social matching and adaptive gaming features. This could be done by stepwise adaption of difficulty in behavioral goals for persuasive systems, as shown in our Rasch-based tailoring. All of these approaches require further systematic long-term analysis of mediating variables.

12.5 Behavior Change

We conclude in chapter 11 that socio-technical systems can create behavior change but struggle to support its maintenance due to frustration, dropout, and boredom. Our long-term study on the *Nutrilize* system further indicates that reasons for falling back into old habits are social constraints, extraordinary events, and favorite food items. The problem of how to achieve more permanent behavior change has also been addressed in recent literature. For example, Pinder et al. (Pinder et al., 2018) emphasize habits and promote detecting, breaking, and reforming habits to achieve long-term behavior change. The authors criticize that many prominent behavior change theories do not acknowledge this but admit that the prerequisite of accurate and fast context and behavior detection remains an unsolved issue. Their idea might be a useful addition to *Nutrilize* since falling back into old habits (e.g., favorite food items) is mentioned as a reason for lack of persistence in behavior changes. Another recent work by Rapp et al. (Rapp et al., 2019) suggests that the measurement of behavior change might not be sufficient to cover all types of human change that is not (yet) expressed in behavior. For example, a user's motivation or underlying reasoning might change but not be visible in the targeted set of variables but instead be expressed in other ways. This kind of effect also appears in the *Nutrilize* evaluation, where users report starting to increase physical activity, although the application did not directly emphasize that. Finally, Nurmi et al. (Nurmi et al., 2020) built an application that supports users in actively steering their behavior change process, including the goal setting and success variables. The authors show that their participants valued the provided autonomy and reflection. In *Nutrilize*, we observe similar processes with, for example, one user reporting changing the internal goal from weight loss to healthiness, which leads to higher short-term success and thus more motivation. Based on the insights provided by these publications and our own studies, we propose to tackle the long-term habit maintenance by integrating relapse events into the system. Suppose the system could anticipate social constraints and extraordinary events. In that case, it could propose strategies to manage the impact with adapted prior or posterior behavior and conscious preparation of in-time decision strategies. In the same way, favorite food items could be included as rewards within the system to avoid uncontrolled relapses.

12.6 Open research challenges

There are open research questions in areas beyond the previously discussed dietary tracking, nutrition games, food recommender systems, personalization for persuasion, and behavior change aspects. These open topics are genotypic personalization of nutrition recommendations, context-dependent timing of feedback, and strategies to provide flexible motivational support via alternative interfaces. Regarding personalized nutrition, a recent work by Food4Me project member John Mathers (Mathers, 2019) discusses the benefits and challenges of personalized nutrition. Although the science behind personalizing nutrition recommendations based on genomics and microbiomes is growing, the interventions providing such advice show little additional impact, with users disregarding the risks presented. The author suggests focusing on other personal elements such as psychological, social, economic, and cultural factors to promote personal dietary changes. Regarding the content of persuasive input in certain contexts, a recent study by Wahl et al. (Wahl et al., 2020) gives insights into the motivational dynamics of eating in different situations. Their work reveals that motives driving a certain food decision depend on the situation shown by the in-moment assessment differing from the general assessment. The authors also show a high user dependency of motivators, which vary in value and variance between users. This situation and user dependency are in line with participants of the *Nutrilize* trial focussing on two general motivators - hunger and appetite - while reporting other motivators when describing their fall-back situations - sociability, stress, habit. These insights suggest that feedback needs to target context-dependent motivators to be effective in changing decisions. Finally, regarding more flexible and user/context adapted interfaces, Elsweiler et al. (Elsweiler et al., 2020) compared different conversational interfaces for healthy eating. The authors conclude that authentic human-like conversations are very unpredictable and challenging to be modeled. In contrast, system-like conversations did not have much of a negative impact on user experience. In the context of this thesis' studies, we attribute the highest relevance between these open issues to the context-dependent delivery of feedback.

12.7 CONCLUSION AND FUTURE PROSPECTS

Further iterations within the design science cycles that were not feasible during the given time are considered starting points for future work. The critical reflection of our results and its comparison with recent literature reveal several future research challenges. The challenges closest to our work are the improvement of dietary tracking with automated systems, the extension of serious games research to cover more insight into successful designs and their dependencies, the expansion of food recommender systems, to include and knowledge modeling, large datasets, and more user context into the algorithm. These issues could be addressed in immediate follow-up studies with improved versions of the design artifacts developed in this thesis. More general research gaps revealed during this work are a need for more personalization of persuasive and gameful features to personality, ability, context, and cultural background and a need for more theory on behavior change, including interactive habit modeling and reformation. These gaps require a considerable amount of fundamental research on the psychological effects that are mediating motivation and behavior. Finally, open research challenges in other disciplines are related to the modeling of biologically personalized nutrition, the modeling and context-dependent assessment of nutrition motivation and decision inhibitors, and the means for communicating this feedback via flexible interfaces such as conversational agents. While these approaches address the same area of interest, as in this thesis, they would require a complete redesign of the socio-technical artifacts used to solve the targeted use cases.

Part V

APPENDIX

A

PRIOR APPEARANCE IN PUBLICATIONS

The following table gives the exact reference and adjustments made for sections whose text is related to prior publications:

Section in Thesis	Prior Publication	Section in Prior Publication	Type of Reference
Section 2.4	(Schäfer et al., 2017a)	State of the Art in Nutrition Modeling	Newly written but based on similar content
Section 2.5	(Schäfer et al., 2017b)	Standing at the Brink + Vision of the Future	Newly written but based on similar content
Section 3.1	(Schäfer et al., 2017)	Introduction	Literal Citations (marked in gray) mixed with new Text
Section 3.2	(Schäfer et al., 2017)	Previous Work on Health Games + Concepts of Games for Health	Literal Citations (marked in gray) mixed with new Text
Section 3.3	(Schäfer et al., 2017)	System Design	Literal Citations (marked in gray) mixed with new Text
Section 4.1	(Schäfer et al., 2018)	Introduction	Literal Citation with minor spelling corrections and adjusted references
Section 4.2	(Schäfer et al., 2018)	Background	Literal Citation with minor spelling corrections and adjusted references
Section 4.3	(Schäfer et al., 2018)	Smartphone Activity Model + Visual Feedback Design	Literal Citation with minor spelling corrections and adjusted references
Section 4.4	(Schäfer et al., 2018)	Study Design + Results	Literal Citation with minor spelling corrections and adjusted references
Section 4.5	(Schäfer et al., 2018)	Discussion of Results	Literal Citation with minor spelling corrections and adjusted references
Section 4.6	(Schäfer et al., 2018)	Conclusion and Future Work	Literal Citation with minor spelling corrections and adjusted references
Section 7.1	(Terzimehić et al., 2016)	Theoretical Background	Newly written but based on similar content
Section 7.2	(Terzimehić et al., 2016)	Theoretical Background	Newly written but based on similar content
Section 8.2.2	(Leipold et al., 2018)	Nutrition Recommender System	Newly written but based on similar content
Section 8.3	(Leipold et al., 2018)	Nutrilize Interface Design	Newly written but based on similar content
Section 8.4	(Leipold et al., 2018)	User Study + Study Results	Newly written but based on similar content
Section 8.5	(Leipold et al., 2018)	Discussion of Results	Newly written but based on similar content
Section 9.1	(Schäfer and Willemsen, 2019)	Introduction (Paragraph 4+5) + Related Work (Paragraph 4+5)	Literal Citation with minor spelling corrections and adjusted references
Section 9.2	(Schäfer and Willemsen, 2019)	Method (Application Design + Rasch Scale)	Literal Citation with minor spelling corrections and adjusted references
Section 9.3	(Schäfer and Willemsen, 2019)	Method (Research Design + Study Procedure + Data Collection) + Results	Literal Citation with minor spelling corrections and adjusted references
Section 9.4	(Schäfer and Willemsen, 2019)	Discussion of Results	Literal Citation with minor spelling corrections and adjusted references
Section 9.5	(Schäfer and Willemsen, 2019)	Conclusion and Future Work	Literal Citation with minor spelling corrections and adjusted references

B
QUESTIONNAIRES OF FOCUS GROUPS

Interviewleitfaden „NUDGE Plattform“ (~90 Min.)

Team bereitet Raum vor (z.B. Protokoll; Etiketten; Stuhlkreis; Waage, Stadiometer; Flyer; Giveaways)

1. Begrüßung & Einführung (~15 Min.)

Assistenz führt Protokoll. CAVE: Einverständniserklärungen (ICs) sichten und ins Protokoll eintragen. ICs verbleiben an den Schulen!

Einleitende Worte des Moderators z.B. Hanna Schäfer (HS), Sophie L. Holzmann (SLH)

- „Hallo zusammen! Vielen Dank, dass ihr in dieser Diskussionsrunde mitmacht
- Ich heiße XXX und ich komme von der Technischen Universität München
- Die letzten Jahre waren wir mit unseren KollegInnen damit beschäftigt, eine digitale Spieleplattform zu entwickeln
- Dieses heißt „NUDGE“
- Die Plattform beinhaltet etwas zum Thema „Ernährung“
- Nach einer kurzen Einführung, dürft ihr die Plattform und eines der Spiele in Videos anschauen. Im Nachgang sprechen wir dann darüber wie es Euch gefallen hat.
- Bevor wir starten, möchte ich kurz ein paar Worte dazu sagen, wie solche Gruppendiskussionen ablaufen
- Jeder darf seine eigene Meinung frei äußern
- Auch wenn Du nicht der Meinung Deines Mitschülers bist, sollst Du Dich melden und Deine Meinung sagen
- Falls Du Dir noch nicht sicher bist, was Du sagen sollst, warte ein wenig ab und melde Dich einfach später

FORTSETZUNG…

- Es ist keine Prüfungssituation, d.h. es geht nicht um richtig oder falsch, sondern es geht um DEINE EIGENE MEINUNG
- Alles, was hier gesprochen wird, bleibt „unter uns“
- Unser Gespräch wird über ein Mikrofon aufgenommen
- Wenn wir zurück in München sind, werden wir die Aufnahme abtippen und es dann auswerten. Diese Daten werden nicht an andere Personen weitergegeben
- Da wir Euch nicht mit Namen, sondern mit einer Nummer ansprechen, weiß am Ende keiner wie ihr heißt
- Beginnen wir damit, dass sich bitte jeder einen Aufkleber mit einer Nummer auf das Oberteil klebt
- Ab sofort spreche ich Euch mit dieser Nummer an

Team führt die Messungen von Körpergröße (Stadiometer) und Körpergewicht (Digitale Waage) durch. Assistenz trägt die Werte zusammen mit Alter, Geschlecht und Klasse in das Protokoll ein. CAVE: Diskretion bei Messung!

Bevor ihr das Spiel spielen könnt, möchte ich Euch ein paar Fragen zu den Themen „Ernährung" und „digitale Spiele" stellen!

2. Ernährung (~5 Min.)

- 2.1 Was bedeutet das Thema „Ernährung" für Euch persönlich?
- 2.2 Wie findet ihr heraus, wie viel Zucker in einem Glas Limo ist?

3. Spielverhalten Smartphone (~5 Min.)

- 3.1 Wofür benutzt ihr Eure Smartphones?
- 3.2 Welche Spiele spielt ihr auf Eurem Smartphone?

4. Spieleplattform allgemein (~5 Min.)

- 4.1 Habt ihr Lust, auf einer Plattform etwas über Ernährung zu lernen?
- 4.2 Wie soll die Spieleplattform aussehen, damit ihr sie nutzen wollt?

Team händigt Smartphones (+Kopfhörer) aus. Tutorial muss auf Bildschirm zu sehen sein!

Jetzt bekommt jeder von Euch ein Smartphone, worauf ihr für eine Minute einen Trailer sehen könnt. Setzt bitte dazu die Kopfhörer auf. Erst wenn ich „Start" sage, dürft ihr alle gleichzeitig anfangen.

Falls Ihr Schwierigkeiten haben solltet, meldet Euch oder sprecht uns an, wir helfen Euch dann sofort. Sind alle soweit? Dann kann es losgehen. Viel Spaß!

5. Smartphone-Session I – Trailer (~10 Min.)

- 5.1 Was ist Euer erster Eindruck von der Spieleplattform?
- 5.2 Würdet ihr die Spieleplattform in Eurer Freizeit nutzen?
- 5.3 Was hat Euch an der Spieleplattform am besten gefallen?
- 5.4 Was hat Euch an der Spieleplattform am wenigsten gefallen?
- 5.5 Warum würdet ihr diese Spieleplattform Euren Freunden (nicht) empfehlen?

Kurz vor Ablauf der Zeit, kündigt der Moderator das baldige Ende an.

enable
healthy food choices in all stages of life
MRI Klinikum rechts der Isar
TUM Technische Universität München
DIE DEUTSCHEN UNIVERSITÄTSKLINIKA

Team sammelt Smartphones ein, entfernt Kopfhörer und bereitet Session II vor.

Moderator kündigt fünf Minuten Pause (6.) an (AUFSICHTSPFLICHT → ZIMMER)

Team bereitet in Pause Session II vor.

7. Smartphone-Session II – Trailer (~15 Min.)

Team händigt Smartphones aus.

Kurz vor Ablauf der Zeit, kündigt der Moderator das baldige Ende an.

Team sammelt Smartphones ein.

So, nun habt ihr unser Spiel gesehen und seid Experten, wenn es darum geht, was gut und schlecht an dem Spiel ist. Dies werden wir in den nächsten 15 Minuten zusammen herausarbeiten. Wir sind schon sehr auf Eure Ideen und Anregungen gespannt.

- 7.1 Was ist Euer erster Eindruck vom Spiel?
- 7.2 Würdet ihr dieses Spiel in Eurer Freizeit spielen?
- 7.3 Was hat Euch am Spiel am besten gefallen?
- 7.4 Was hat Euch an dem Spiel nicht gefallen?
- 7.5 Sagt bitte in einem Satz, was ihr Euren Freunden & Eltern über das Spiel erzählen werdet

Toll, vielen Dank für die super Anmerkungen von Euch. Nachdem wir jetzt wissen, was gut und schlecht an unserem Spiel ist, möchten wir auch noch wissen, ob ihr das Spiel auch selbst spielen würdet. Also…

8. Intention to Use (~10 Min.)

- 8.1 Was glaubt ihr wie das Spiel funktioniert?
- 8.2 Würdet ihr das Spiel in Zukunft spielen?
- 8.3 Warum würdet ihr das Spiel (nicht) weiter nutzen?

- 8.4 Wie lange würdet ihr das Spiel nutzen wollen?

Allmählich sind wir am Ende unserer Diskussionsrunde. Wollt ihr noch etwas loswerden (10.)?

9. Vergleich mit anderen Spielen und Spielideen (~10 Min.)

- 9.1 Wie ist das Spiel im Vergleich zu anderen Spielen, die ihr kennt?
- 9.2 Was sind für euch die wichtigsten Elemente in einem Ernährungsspiel?
- 9.3 Welche weiteren Spiele könnt ihr euch für eine Ernährungsplattform vorstellen?

10. Dank & Verabschiedung

Vielen Dank an jeden Einzelnen von Euch für Eure Hilfe und Eure tollen Beiträge. Wir wünschen Euch einen tollen Tag!

Team teilt Flyer (1x) und Giveaways (2x) aus!

Team stellt ursprüngliche Ordnung im Raum wieder her.

Interviewleitfaden „Fit, Food, Fun“ Spiel (~90 Min.)

Team bereitet Raum vor (z.B. Protokoll; Etiketten; Stuhlkreis; Waage, Stadiometer; Flyer; Giveaways)

1. Begrüßung & Einführung (~15 Min.)

Assistenz führt Protokoll. CAVE: Einverständniserklärungen (ICs) sichten und ins Protokoll eintragen. ICs verbleiben an den Schulen!

Einleitende Worte des Moderators z.B. Hanna Schäfer (HS), Sophie L. Holzmann (SLH)

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- Ich heiße XXX und ich komme von der Technischen Universität München
- Die letzten Jahre waren wir mit unseren KollegInnen damit beschäftigt, ein digitales Ernährungsspiel zu entwickeln
- Dieses heißt „Fit, Food, Fun“
- Das Spiel beinhaltet etwas zum Thema „Ernährung“
- Dieses Spiel haben wir heute für Euch dabei
- Nach einer kurzen Einführung, dürft ihr das Spiel auf Tablets spielen, im Nachgang sprechen wir dann darüber, wie es Euch gefallen hat
- Bevor wir starten, möchte ich kurz ein paar Worte dazu sagen, wie solche Gruppendiskussionen ablaufen
- Jeder darf seine eigene Meinung frei äußern
- Auch wenn Du nicht der Meinung Deines Mitschülers bist, sollst Du Dich melden und Deine Meinung sagen
- Falls Du Dir noch nicht sicher bist, was Du sagen sollst, warte ein wenig ab und melde Dich einfach später

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- Alles, was hier gesprochen wird, bleibt „unter uns“
- Unser Gespräch wird über ein Mikrofon aufgenommen
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- Da wir Euch nicht mit Namen, sondern mit einer Nummer ansprechen, weiß am Ende keiner wie ihr heißt
- Beginnen wir damit, dass sich bitte jeder einen Aufkleber mit einer Nummer auf das Oberteil klebt
- Ab sofort spreche ich Euch mit dieser Nummer an

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Bevor ihr das Spiel spielen könnt, möchte ich Euch ein paar Fragen zu den Themen „Ernährung“ und „digitale Spiele“ stellen!

2. Ernährung (~5 Min.)

- 2.1 Was bedeutet das Thema „Ernährung“ für Euch persönlich?
- 2.2 Wie findet ihr heraus, wie viel Zucker in einem Glas Limo ist?

3. Spielverhalten Smartphone (~5 Min.)

- 3.1 Wofür benutzt ihr Eure Smartphones?
- 3.2 Welche Spiele spielt ihr auf Eurem Smartphone?

4. Ernährungsspiel allgemein (~5 Min.)

- 4.1 Habt ihr Lust ein Spiel zu spielen, um dabei etwas über Ernährung zu lernen?
- 4.2 Wie soll das Spiel aussehen, damit ihr es spielen wollt?

Team händigt Smartphones (+Kopfhörer) aus. Tutorial muss auf Bildschirm zu sehen sein!

Jetzt bekommt jeder von Euch ein Smartphone, worauf ihr für eine Minute einen Trailer sehen könnt. Setzt bitte dazu die Kopfhörer auf. Erst wenn ich „Start“ sage, dürft ihr alle gleichzeitig anfangen.
Falls Ihr Schwierigkeiten haben solltet, meldet Euch oder sprecht uns an, wir helfen Euch dann sofort. Sind alle soweit? Dann kann es losgehen. Viel Spaß!

5. Smartphone-Session I – Trailer (~10 Min.)

- 5.1 Was ist Euer erster Eindruck vom Spiel?
- 5.2 Würdet ihr dieses Spiel in Eurer Freizeit spielen?
- 5.3 Würdet ihr das Spiel Euren Freunden empfehlen?

Kurz vor Ablauf der Zeit, kündigt der Moderator das baldige Ende an.

Team sammelt Smartphones ein, entfernt Kopfhörer und bereitet Session II vor.

Moderator kündigt fünf Minuten Pause (6.) an (AUFSICHTSPFLICHT → ZIMMER)

Team bereitet in Pause Session II vor.

7. Smartphone-Session II mit ergänzendem Print-Tutorial (~15 Min.)

Willkommen zurück. Nun beginnt der zweite Teil der Diskussionsrunde. Jetzt bekommt ihr wieder das Smartphone und dürft darauf das Spiel „Fit, Food, Fun“ für 15 Min. spielen.

Team händigt Smartphones (-Kopfhörer) & Print-Tutorials aus. Spiel muss auf Bildschirm zu sehen sein!

Bitte beginnt noch nicht mit dem Spielen und wartet bitte bis ich „Start“ sage, dann könnt ihr mit dem Spielen loslegen.
Falls Ihr Schwierigkeiten haben solltet, meldet Euch oder sprecht uns an, wir helfen Euch dann sofort. Sind alle soweit? Dann kann es losgehen. Viel Spaß!

Kurz vor Ablauf der Zeit, kündigt der Moderator das baldige Ende an.

Team sammelt Smartphones ein.

8. Spielerlebnis (~15 Min.)

So, nun habt ihr unser Spiel gespielt und seid Experten, wenn es darum geht, was gut und schlecht an dem Spiel ist. Dies werden wir in den nächsten 15 Minuten zusammen herausarbeiten. Wir sind schon sehr auf Eure Ideen und Anregungen gespannt.

- 8.1 Was hat Euch am Design (z.B. Farbe, Grafiken) des Spiels gefallen?
- 8.2 Was hat Euch NICHT am Design (z.B. Farbe, Grafiken) des Spiels gefallen?
- 8.3 Was hat Euch am Spiel am besten gefallen?
- 8.4 Was hat Euch am Spiel am wenigsten gefallen?
- 8.5 Womit hattet ihr Schwierigkeiten im Spiel (z.B. Verständnis/Handhabung)?
- 8.6 Was wusstet ihr über Ernährung vor dem Spielen nicht, aber jetzt schon?

- 8.7 8.7 Sagt bitte in einem Satz, was ihr Euren Freunden & Eltern über das Spiel erzählen werdet?

Toll, vielen Dank für die super Anmerkungen von Euch. Nachdem wir jetzt wissen, was gut und schlecht an unserem Spiel ist, möchten wir auch noch wissen, ob ihr das Spiel auch selbst spielen würdet. Also…

9. Intention to Use (~10 Min.)

- 9.1 Würdet ihr das Spiel in Zukunft spielen?
- 9.2 Warum würdet ihr das Spiel (nicht) weiter spielen?
- 9.3 Wie lange würdet ihr das Spiel spielen?
- 9.4 Wie ist das Spiel im Vergleich zu anderen Spielen, die ihr kennt?

Allmählich sind wir am Ende unserer Diskussionsrunde. Wollt ihr noch etwas loswerden (10.)?

11. Dank & Verabschiedung

Vielen Dank an jeden Einzelnen von Euch für Eure Hilfe und Eure tollen Beiträge. Wir wünschen Euch einen tollen Tag!

Team teilt Flyer (1x) und Giveaways (2x) aus!

Team stellt ursprüngliche Ordnung im Raum wieder her.

C

QUESTIONNAIRES OF AVATAR STUDY

Fragebogen

Trage hier bitte den Code, der auf deinem Akzelerometer steht, ein:

Code: ________

Bist du ein ☐ Mädchen oder ein ☐ Junge?

Welchen Beruf übt deine Mutter aus?

………………………………………………………………

Was macht deine Mutter in diesem Beruf?

……
……

Welchen Beruf übt dein Vater aus?

………………………………………………………………

Was macht dein Vater in diesem Beruf?

……
……

Welche Sprache sprichst du hauptsächlich mit deinen Eltern?

- ☐ Deutsch
- ☐ Andere Sprache und zwar ….

Welche Sprache sprichst du hauptsächlich mit deinen Freunden?

- ☐ Deutsch
- ☐ Andere Sprache und zwar ….

Ich mache Sport, weil…

	Stimme überhaupt nicht zu	Stimme eher nicht zu	teils/teils	Stimme eher zu	Stimme voll und ganz zu
…andere sagen, dass ich Sport machen sollte.	❑	❑	❑	❑	❑
…ich ein schlechtes Gewissen habe, wenn ich keinen Sport mache.	❑	❑	❑	❑	❑
…ich die Vorteile von Sport gut finde.	❑	❑	❑	❑	❑
…weil es Spaß macht.	❑	❑	❑	❑	❑
Ich sehe nicht ein, warum ich Sport machen sollte.	❑	❑	❑	❑	❑
…meine Freunde / Familie sagen, dass ich Sport machen sollte.	❑	❑	❑	❑	❑
…ich mich schäme, wenn ich eine Zeit lang keinen Sport gemacht habe.	❑	❑	❑	❑	❑
…es mir wichtig ist, regelmäßig Sport zu machen.	❑	❑	❑	❑	❑
Ich sehe nicht ein, warum ich mir die Mühe machen sollte, Sport zu machen.	❑	❑	❑	❑	❑
…ich es genieße Sport zu machen.	❑	❑	❑	❑	❑
…andere nicht zufrieden mit mir wären, wenn ich nicht Sport machen würde.	❑	❑	❑	❑	❑
Ich sehe keinen Sinn in Sport.	❑	❑	❑	❑	❑
…ich mich wie ein Versager fühle, wenn ich länger keinen Sport gemacht habe.	❑	❑	❑	❑	❑
…es wichtig ist, sich die Mühe zu geben, regelmäßig Sport zu machen.	❑	❑	❑	❑	❑
…Sport für mich eine angenehme Aktivität ist.	❑	❑	❑	❑	❑
…ich mich von meinen Freunden / meiner Familie unter Druck gesetzt fühle, Sport zu machen.	❑	❑	❑	❑	❑
…ich unruhig werde, wenn ich nicht regelmäßig Sport mache.	❑	❑	❑	❑	❑
… ich Freude und Zufriedenheit erfahre, wenn ich Sport mache.	❑	❑	❑	❑	❑
Ich denke, Sport machen ist Zeitverschwendung.	❑	❑	❑	❑	❑

Sport zu machen...	Stimme überhaupt nicht zu	Stimme eher nicht zu	teils/teils	Stimme eher zu	Stimme voll und ganz zu
…bereitet mir Freude.	❑	❑	❑	❑	❑
…finde ich langweilig.	❑	❑	❑	❑	❑
…mag ich nicht.	❑	❑	❑	❑	❑
…genieße ich.	❑	❑	❑	❑	❑
…macht überhaupt keinen Spaß.	❑	❑	❑	❑	❑
…gibt mir Energie.	❑	❑	❑	❑	❑
…macht mich deprimiert.	❑	❑	❑	❑	❑
…ist sehr angenehm.	❑	❑	❑	❑	❑
…bedeutet, dass mein Körper sich gut anfühlt.	❑	❑	❑	❑	❑
…gibt mir etwas.	❑	❑	❑	❑	❑
…ist sehr aufregend.	❑	❑	❑	❑	❑
…frustriert mich.	❑	❑	❑	❑	❑
…ist überhaupt nicht interessant.	❑	❑	❑	❑	❑
…gibt mir ein starkes Erfolgserlebnis.	❑	❑	❑	❑	❑
…fühlt sich gut an.	❑	❑	❑	❑	❑
…gibt mir das Gefühl, dass ich lieber etwas anderes machen würde.	❑	❑	❑	❑	❑

	Stimme überhaupt nicht zu	Stimme eher nicht zu	teils/teils	Stimme eher zu	Stimme voll und ganz zu
Ich kann mir selbst aussuchen, welchen Sport ich machen möchte.	❑	❑	❑	❑	❑
Beim Sport habe ich das Gefühl, dass die Leute, die ich mag, auch mich mögen.	❑	❑	❑	❑	❑
Ich bin gut in Sport.	❑	❑	❑	❑	❑
Ich mache genau den Sport, den ich wirklich machen will.	❑	❑	❑	❑	❑
Wenn ich Sport mache, fühle ich mich mit den Menschen verbunden, die mich mögen und die ich auch mag.	❑	❑	❑	❑	❑
Ich bin talentiert in Sport.	❑	❑	❑	❑	❑
Der Sport, den ich mache, passt wirklich gut zu mir.	❑	❑	❑	❑	❑
Beim Sport fühle ich mich mit den Menschen verbunden, die mir wichtig sind.	❑	❑	❑	❑	❑
Beim Sport schaffe ich das, was ich mir vorgenommen habe.	❑	❑	❑	❑	❑
Ich habe schon immer den Sport gemacht, der mich wirklich interessiert.	❑	❑	❑	❑	❑
Ich verstehe mich mit den Menschen, mit denen ich Sport mache, sehr gut.	❑	❑	❑	❑	❑
Ich kann auch schwierige sportliche Aufgaben meistern.	❑	❑	❑	❑	❑

	Stimme überhaupt nicht zu	Stimme eher nicht zu	teils/teils	Stimme eher zu	Stimme voll und ganz zu
In meiner Freizeit kann ich an den meisten Tagen Sport machen.	❑	❑	❑	❑	❑
Ich kann meine Eltern oder andere Erwachsene fragen, ob sie gemeinsam mit mir Sport machen.	❑	❑	❑	❑	❑
In meiner Freizeit kann ich an den meisten Tagen Sport machen, auch wenn ich stattdessen Fernsehen schauen oder Videospiele spielen könnte.	❑	❑	❑	❑	❑
In meiner Freizeit kann ich an den meisten Tagen Sport machen, auch wenn es sehr warm oder kalt draußen ist.	❑	❑	❑	❑	❑
In meiner Freizeit kann ich an den meisten Tagen meinen besten Freund/meine beste Freundin fragen, gemeinsam mit mir Sport zu machen.	❑	❑	❑	❑	❑
In meiner Freizeit kann ich an den meisten Tagen Sport machen, auch wenn ich zuhause bleiben muss.	❑	❑	❑	❑	❑
Ich kann mir meine Zeit gut einteilen, um in meiner Freizeit an den meisten Tagen Sport zu machen.	❑	❑	❑	❑	❑
In meiner Freizeit kann ich an den meisten Tagen Sport machen, egal wie stressig der Tag ist.	❑	❑	❑	❑	❑

Während einer typischen Woche, wie oft…	niemals	einmal	häufiger als einmal	fast jeden Tag	jeden Tag
…ermutigen dich deine Freunde Sport zu machen?	❑	❑	❑	❑	❑
…machen deine Freunde Sport mit dir?	❑	❑	❑	❑	❑
…sagen dir deine Freunde, dass du sportlich bist?	❑	❑	❑	❑	❑

Während einer typischen Woche, wie oft…	niemals	einmal	häufiger als einmal	fast jeden Tag	jeden Tag
…macht ein Familienmitglied Sport mit dir?	❑	❑	❑	❑	❑
… bringt dich ein Familienmitglied dorthin, wo du Sport machen kannst?	❑	❑	❑	❑	❑
…schaut dir ein Familienmitglied zu, während du Sport machst?	❑	❑	❑	❑	❑
… sagt dir ein Familienmitglied, dass du sportlich bist?	❑	❑	❑	❑	❑

Beim Sportunterricht, wie oft…	niemals	ab und zu	oft	fast jede Sport-stunde	jede Sport-stunde
… ermutigt dich dein Sportlehrer Sport in deiner Freizeit zu machen?	❑	❑	❑	❑	❑
…lobt dich dein Sportlehrer während des Sportunterrichts?	❑	❑	❑	❑	❑
… informiert dich dein Sportlehrer über Möglichkeiten, außerhalb der Schule Sport zu machen (z.B. Vereine, Tanzschule etc.)?	❑	❑	❑	❑	❑
… bietet dein Sportlehrer für dich passende Sportarten während des Sportunterrichts an?	❑	❑	❑	❑	❑
… hat dein Sportlehrer Ideen, wie du in deiner Freizeit Sport machen kannst?	❑	❑	❑	❑	❑

D

QUESTIONNAIRES OF FIT FOOD FUN PILOT STUDY

These are the pre-study and post-study questionnaires of the game group. The control group questionnaires are identical in structure minus the questions on the game in the post-study questionnaires. For some questionnaires such as the IMI, the word game has been exchanged with teaching in the control group.

Pilotstudie „Fit, Food, Fun"

- B E F R A G U N G **T E I L 1** (MONTAG) -

[Nachfolgende Seiten werden von den SchülerInnen am Studienort ausgefüllt]

Geschlecht:

__ weiblich

__ männlich

Studien-ID: ______

Liebe Schülerin, lieber Schüler,

in diesem Fragebogen geht es nicht um richtige oder falsche Antworten oder um Noten. Es geht darum, dass Du uns Deine eigene Meinung und Deine eigenen Gedanken mitteilst. Bitte fülle den Fragebogen sorgfältig und vollständig aus. Nimm` Dir Zeit und lies` Dir die Fragen gründlich durch. Sprich` Dich bitte nicht mit Deinem Nachbarn/Deiner Nachbarin ab.
Vielen Dank, dass Du bei unserer Studie mitmachst.

Dein Studienteam der Technischen Universität München

1. Ernährung

1.1 Wenn Du etwas isst, wie wichtig ist es für Dich, dass das Nahrungsmittel gesund ist?
Bitte kreuze die Aussage an, die auf Dich am besten zutrifft! *Nur 1 Antwort ist möglich.*

- ☐ Sehr wichtig
- ☐ Wichtig
- ☐ Eher wichtig
- ☐ Eher unwichtig
- ☐ Unwichtig
- ☐ Völlig unwichtig

1.2 Welche der folgenden Aussage trifft auf Dich zu? *Nur 1 Antwort ist möglich.*

- ☐ Ich achte darauf, mich gesund zu ernähren.
- ☐ Ich achte nicht darauf, mich gesund zu ernähren.

1.3 In meiner täglichen Ernährung achte ich auf…
Bitte kreuze die Aussagen an, die auf Dich am besten zutreffen! *Mehrere Antworten sind möglich.*

- ☐ Eiweiß
- ☐ Zucker
- ☐ Fett
- ☐ Obst
- ☐ Gemüse
- ☐ Wasser
- ☐ Kalorien
- ☐ Sonstiges: ___________________
- ☐ Keine Antwort trifft zu

1.4 Bitte vervollständige die folgende Ernährungsregel, indem Du die fehlenden Wörter ergänzt. *Pro Freifeld kannst Du ein Wort ergänzen.*

__________*wählen: Bei Getreideprodukten wie Brot, Nudeln, Reis und Mehl ist die* __________*variante die beste Wahl für Deine Gesundheit. Lebensmittel aus*__________*sättigen länger und enthalten*__________*Nährstoffe als Weißmehlprodukte.*

1.5 Wie häufig isst Du die aufgeführten Nahrungsmittel?

Bitte pro Zeile jeweils einmal ein Kästchen ankreuzen!

Wie häufig isst Du die aufgeführten Nahrungsmittel:	*Skala*	nie	selten	mehrmals pro Monat	mehrmals pro Woche	täglich
1. dunkles Brot oder Brötchen (Vollkorn, Roggen)	A	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
2. Kuchen, Teilchen, Plätzchen	D	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
3. Butter (keine Margarine)	F	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
4. fettarme Margarine	F/H	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
5. Marmelade, Honig	D	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
6. Nussnougat-Cremes	D	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
7. fettarme Wurst	E/H	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
8. „normale“ Wurst	E	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
9. Quark	C	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
10. Joghurt	C	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
11. fettarmer Käse (Light-Käse)	C/H	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
12. „normaler“ Käse	C	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
13. Obst, Früchte	B	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
14. Schokolade, Pralinen, Bonbons	D	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
15. Schokoriegel, süße Pausensnacks	D	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
16. Chips, Salzgebäck, Nüsse	G	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
17. Kartoffeln (Salz-, Pellkartoffeln)	A	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
18. Nudeln	A	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
19. Reis	A	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
20. Gemüse	B	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
21. Salat	B	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5

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22. Rindfleisch, Kalbfleisch (Rouladen, Rinderbraten, Kalbsgulasch)	E	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
23. Schweinefleisch (Schweinebraten, Gulasch)	E	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
24. Fisch (Forelle, Karpfen, Fischfilets, Fischstäbchen)	E	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
25. Geflügel, Hühner-Frikassee, Geflügelstäbchen	E	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
26. Hamburger, Big Mac	G	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
27. Pommes frites, Kartoffelecken	G	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
28. Bratwurst, Currywurst, Grillhähnchen	G	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
29. Döner, Gyros u. Ä.	G	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
30. Pizza-, China-Imbiss	G	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
31. Tiefkühl-Pizza, Tiefkühl- oder Mikrowellengerichte, Dosen, Tüten	G	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5

Quelle: Beckert-Zieglschmid, C., Brähler, E. (2007). Der Leipziger Lebensstilfragebogen für Jugendliche (LLfJ). Ein Instrument zur Arbeit mit Jugendlichen. Das Handbuch. Göttingen: Vandenhoeck & Ruprecht.

1.6 Bitte vervollständige die folgende Ernährungsregel, indem Du die fehlenden Wörter ergänzt. *Pro Freifeld kannst Du ein Wort ergänzen.*

__________und Salz einsparen: Mit__________gesüßte Lebensmittel und Getränke sind __________empfehlenswert. Vermeide diese möglichst und setze__________sparsam ein. Spare Salz und reduziere den Anteil salzreicher Lebensmittel.

1.7 Wie häufig trinkst Du die aufgeführten Getränke?

Bitte pro Zeile jeweils einmal ein Kästchen ankreuzen!

Wie häufig trinkst Du die aufgeführten Getränke:	*Skala*	nie	selten	mehrmals pro Monat	mehrmals pro Woche	täglich
34. Vollmilch, Kakao	D	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
35. fettarme Milch	E	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
36. Joghurt- oder Milchgetränke (Erdbeer, Vanille, Schoko...)	D	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
37. Kaffee, schwarzer Tee	C	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
38. Kräutertee, Früchtetee	E	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
39. Cola, Limonade	B	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
40. Light-Cola, Light-Limonade, Light-Fruchtsaft, Wasser mit Geschmack	B	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
41. Fruchtsäfte (Orangensaft, Apfelsaft, …)	D	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
42. Mineralwasser, Wasser	E	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
43. Power-, Energydrinks (Red Bull, Flying Horse)	B	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
44. Bier	A	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
45. Wein, Sekt, Prosecco	A	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
46. Spirituosen (Schnaps, Whisky, Cognac, Korn)	A	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
47. alkoholische Mixgetränke, Cocktails, Alcopops	A	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5

Quelle: Beckert-Zieglschmid, C., Brähler, E. (2007). Der Leipziger Lebensstilfragebogen für Jugendliche (LLfJ). Ein Instrument zur Arbeit mit Jugendlichen. Das Handbuch. Göttingen: Vandenhoeck & Ruprecht.

1.8 Was steckt hinter dem Begriff „Kalorien“ bzw. was ist ein anderer Begriff für Kalorien? *Nur 1 Antwort ist möglich.*

- ☐ Muskelmasse
- ☐ Energie
- ☐ Hunger
- ☐ Durst
- ☐ Weiß nicht

1.9 Was ist ein anderes Wort für Eiweiß? *Schreibe Deine Antwort ins Kästchen!*

1.10 Bitte vervollständige die folgende Ernährungsregel, indem Du die fehlenden Wörter ergänzt. *Pro Freifeld kannst Du ein Wort ergänzen.*

Gesundheitsfördernde Fette nutzen: Bevorzuge__________Öle wie Rapsöl und daraus hergestellte Streichfette. Vermeide__________Fette. Fett steckt oft „unsichtbar“ in verarbeiteten Lebensmitteln wie__________, Gebäck, Süßwaren, Fast-Food und__________.

1.11 Ist Zucker ein Kohlenhydrat? *Nur 1 Antwort ist möglich.*

- ☐ Ja
- ☐ Nein
- ☐ Weiß nicht

1.12 Wie viele Portionen Obst und Gemüse sollte man täglich essen (eine Portion = eine Handvoll)? _Nur 1 Antwort ist möglich._

- ☐ 0 Portionen
- ☐ 1-2 Portionen
- ☐ 5 Portionen
- ☐ So viele Portionen wie man möchte
- ☐ Weiß nicht

1.13 Welche der folgenden Aussagen ist richtig? _Nur 1 Antwort ist möglich._

In der täglichen Ernährung sollte man…

- ☐ Zucker einsparen, Salz hingegen darf man so viel essen wie man möchte.
- ☐ Salz einsparen, Zucker hingegen darf man so viel essen wie man möchte.
- ☐ Weder Salz noch Zucker einsparen.
- ☐ Zucker und Salz einsparen.
- ☐ Weiß nicht

1.14 Bitte vervollständige die folgende Ernährungsregel, indem Du die fehlenden Wörter ergänzt. _Pro Freifeld kannst Du ein Wort ergänzen._

Auf das Gewicht achten und in__________bleiben: Vollwertige__________und körperliche__________gehören zusammen. Dabei ist nicht nur regelmäßiger Sport hilfreich, sondern auch ein aktiver Alltag. Pro Tag 30 bis__________Minuten moderate körperliche Aktivität fördert Deine Gesundheit.

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1.15 Stell Dir vor, Du bist in einer Bäckerei und möchtest ein Brot kaufen. Es gibt ein weißes Brot (aus Weißmehl) und ein dunkles Brot (aus Vollkornmehl). Beide Brote haben den gleichen Preis und sehen lecker aus. Welches Brot würdest Du kaufen?

Nur 1 Antwort ist möglich.

- ☐ Dunkles Brot (aus Vollkornmehl)
- ☐ Weißes Brot (aus Weißmehl)
- ☐ Ich esse kein Brot.

1.16 Welche der folgenden Aussagen ist richtig? _Nur 1 Antwort ist möglich._

- ☐ Vollkornbrot enthält mehr Nährstoffe (z.B. Ballaststoffe) als Weißbrot <u>UND</u> sättigt mehr als Weißbrot.
- ☐ Weißbrot enthält mehr Nährstoffe (z.B. Ballaststoffe) als Vollkornbrot.
- ☐ Weißbrot und Vollkornbrot unterscheiden sich hinsichtlich der Nährstoffe (z.B. Ballaststoffe) <u>UND</u> der Sättigung nicht.
- ☐ Weiß nicht

1.17 Welches der folgenden Lebensmittel hat <u>bei gleicher Menge</u> den höchsten Fettgehalt? _Nur 1 Antwort ist möglich._

- ☐ Schokolade
- ☐ Hartkaramellen/Bonbons
- ☐ Gummibärchen
- ☐ Müsli-Riegel
- ☐ Marshmallows
- ☐ Weiß nicht

1.18 Welche der folgenden Aussagen ist richtig? *Nur 1 Antwort ist möglich.*

- ☐ Obst und Gemüse enthalten bei gleicher Menge gleich viel Zucker.
- ☐ Gemüse enthält bei gleicher Menge weniger Zucker als Obst.
- ☐ Obst enthält bei gleicher Menge weniger Zucker als Gemüse.
- ☐ Weiß nicht

1.19 Bitte vervollständige die folgende Ernährungsregel, indem Du die fehlenden Wörter ergänzt. *Pro Freifeld kannst Du ein Wort ergänzen.*

Am besten__________trinken: Trinke rund_____Liter jeden Tag. Am besten__________oder andere kalorienfreie Getränke wie ungesüßten Tee. Zuckergesüßte und alkoholische Getränke sind__________empfehlenswert.

1.20 Welches der folgenden Lebensmittel hat bei gleicher Menge den höchsten Zuckergehalt? *Nur 1 Antwort ist möglich.*

- ☐ Softdrinks (z.B. Limonade, Cola)
- ☐ Wasser
- ☐ Kuhmilch
- ☐ Saftschorle
- ☐ Tomatensaft
- ☐ Weiß nicht

1.21 Welche der folgenden Aussagen ist richtig? *Nur 1 Antwort ist möglich.*

Eiweiß ist besonders viel enthalten in…

- ☐ Butterschmalz
- ☐ Gurke
- ☐ Pizza
- ☐ Lakritze
- ☐ Thunfisch
- ☐ Weiß nicht

1.22 Bitte vervollständige die folgende Ernährungsregel, indem Du die fehlenden Wörter ergänzt. *Pro Freifeld kannst Du ein Wort ergänzen.*

Gemüse und__________– nimm „5 am Tag“: Genieße mindestens_____Portionen Gemüse und_____Portionen__________am Tag.

1.23 Für was steht die Abkürzung DGE? *Nur 1 Antwort ist möglich.*

- ☐ Deutsche Genossenschaft für Ernährung
- ☐ Deutsche Gesellschaft für Erderwärmung
- ☐ Deutsche Gesellschaft für Ernährungsweisen
- ☐ Deutsche Gesellschaft für Ernährung
- ☐ Weiß nicht

2. Sport

2.1 Wie oft machst Du im Winter in der Woche Sport? *Nur 1 Antwort ist möglich.*

- ☐ Regelmäßig mehr als 2 Stunden
- ☐ Regelmäßig 1 bis 2 Stunden
- ☐ Regelmäßig weniger als 1 Stunde
- ☐ Keine sportliche Betätigung

2.2 Wie oft machst Du im Sommer in der Woche Sport? *Nur 1 Antwort ist möglich.*

- ☐ Regelmäßig mehr als 2 Stunden
- ☐ Regelmäßig 1 bis 2 Stunden
- ☐ Regelmäßig Weniger als 1 Stunde
- ☐ Keine sportliche Betätigung

2.3 Wie viele Kalorien [kcal] verbrauchst Du ungefähr, wenn Du 2 Stunden bei mittlerer Anstrengung Fahrrad fährst? *Nur 1 Antwort ist möglich.*

- ☐ Weniger als 200 kcal
- ☐ 600 – 1000 kcal
- ☐ Mehr als 1000 kcal
- ☐ Weiß nicht

2.4 Bei welcher der folgenden drei Sportarten verbrauchst Du bei gleicher Durchführung (z.B. Dauer, Strecke) die meiste Energie? *Nur 1 Antwort ist möglich.*

- ☐ Radfahren
- ☐ Laufen/Jogging
- ☐ Schwimmen
- ☐ Weiß nicht

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3. Persönlichkeit

3.1 Wie verhältst Du Dich in deinem Alltag? Gib für jede Aussage an, wie sehr sie auf Dich zutrifft. *Bitte pro Zeile jeweils ein Kästchen ankreuzen!*

	Trifft überhaupt nicht zu	Trifft eher nicht zu	Weder noch	Eher zutreffend	Trifft voll und ganz zu
Ich bin eher zurückhaltend, reserviert.	○	○	○	○	○
Ich schenke anderen leicht Vertrauen, glaube an das Gute im Menschen.	○	○	○	○	○
Ich bin bequem, neige zur Faulheit.	○	○	○	○	○
Ich bin entspannt, lasse mich durch Stress nicht aus der Ruhe bringen.	○	○	○	○	○
Ich habe nur wenig künstlerisches Interesse.	○	○	○	○	○
Ich gehe aus mir heraus, bin gesellig.	○	○	○	○	○
Ich neige dazu, andere zu kritisieren.	○	○	○	○	○
Ich erledige Aufgaben gründlich.	○	○	○	○	○
Ich werde leicht nervös und unsicher.	○	○	○	○	○
Ich habe eine aktive Vorstellungskraft, bin fantasievoll.	○	○	○	○	○

3.2 Wie verhältst Du Dich gegenüber anderen Menschen? Gib für jede Aussage an, wie sehr sie auf Dich zutrifft. *Bitte pro Zeile jeweils ein Kästchen ankreuzen!*

	Stimme überhaupt nicht zu						Stimme voll und ganz zu
Ich erwidere einen Gefallen immer.	○	○	○	○	○	○	○
Wenn jemand etwas für mich tut, versuche ich etwas von ähnlichem Wert zu tun, um den Gefallen zu erwidern.	○	○	○	○	○	○	○
Ich glaube, dass seltene Produkte wertvoller sind als Massenprodukte.	○	○	○	○	○	○	○
Produkte, die schwer zu bekommen sind, stellen einen besonderen Wert dar.	○	○	○	○	○	○	○
Ich tendiere sehr dazu, auf Autoritätspersonen zu hören.	○	○	○	○	○	○	○
Ich bin eher geneigt, auf eine Autoritätsperson zu hören als auf einen Gleichaltrigen.	○	○	○	○	○	○	○
Wenn ich mich zu einem Termin verpflichte, halte ich mich immer daran.	○	○	○	○	○	○	○
Sobald ich mich verpflichtet habe, etwas zu tun, werde ich es sicherlich tun.	○	○	○	○	○	○	○
Wenn jemand aus meinem sozialen Netzwerk mich über ein gutes Buch informiert, neige ich dazu es zu lesen.	○	○	○	○	○	○	○
Ich verlasse mich oft darauf, dass die anderen Leute wissen, was ich tun soll.	○	○	○	○	○	○	○
Ich tue Leuten, die ich mag, einen Gefallen.	○	○	○	○	○	○	○
Die Meinungen von Freunden sind wichtiger als die Meinungen anderer.	○	○	○	○	○	○	○

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3.3 Wie verhältst Du Dich in Spielen? Bitte entscheide Dich für jede der folgenden Spielerfahrungen für "Ich liebe es", "Ich mag es", "Es ist okay", "Ich mag es nicht", "Ich hasse es". Dabei beziehen sich diese Erfahrungen auf Deine allgemeinen Vorlieben in Bezug auf Spielerfahrungen. *Bitte pro Zeile jeweils ein Kästchen ankreuzen!*

	Ich hasse es	Ich mag es nicht	Es ist okay	Ich mag es	Ich liebe es
Erkunden, um zu sehen was man finden kann.	○	○	○	○	○
Umherschauen, nur um die Landschaft zu genießen.	○	○	○	○	○
Sich wundern, was sich hinter einer verschlossenen Tür befindet.	○	○	○	○	○
Vor einem gefährlichen Feind fliehen.	○	○	○	○	○
Sich erschrocken fühlen.	○	○	○	○	○
Erleichtert fühlen, wenn man in einen sicheren Bereich entkommen konnte.	○	○	○	○	○
Sich aufgeregt fühlen.	○	○	○	○	○
Die Kontrolle unter hoher Geschwindigkeit zu behalten.	○	○	○	○	○
Von einem hohen Felsvorsprung herunterhängen.	○	○	○	○	○
Ein herausforderndes Rätsel lösen.	○	○	○	○	○
Eine vielversprechende Strategie entwickeln.	○	○	○	○	○
Von allein auf eine Lösung kommen.	○	○	○	○	○
Endlich einen schweren Endgegner besiegen.	○	○	○	○	○
Es mit einem starken menschlichen Gegner in einem Wettkampf aufnehmen.	○	○	○	○	○
Das Abschließen einer harten Herausforderung, an der man oft gescheitert ist.	○	○	○	○	○

Ein Gespräch mit Nichtspieler-Charakteren führen.	○	○	○	○	○
Gespräche mit anderen Spielern führen.	○	○	○	○	○
Mit Fremden zusammenarbeiten.	○	○	○	○	○
Jedes Sammelobjekt in einem Bereich aufsammeln.	○	○	○	○	○
Einen Gegenstand finden, der für die Komplettierung einer Sammlung nötig ist.	○	○	○	○	○
100% erreichen.	○	○	○	○	○

3.4 Wie verhältst Du Dich in Spielen? Bringe folgende Spielerfahrungen in eine Rangfolge von 1 ("gefällt mir am meisten") bis 7 ("gefällt mir am wenigsten"). Alle Deine Antworten müssen unterschiedlich sein, und müssen zugeordnet sein.
Bitte nummeriere jede Box in der Reihenfolge Deiner Vorliebe.

	Nummer
Ein Moment des Staunens oder von Schönheit, bei dem einen die Kinnlade herunterklappt.	
Ein Moment der Angst während einer Flucht bei der einem das Herz stehen bleibt.	
Ein Moment der atemberaubenden Geschwindigkeit oder schwindelnden Höhe.	
Der Moment, in dem einem die Lösung eines schwierigen Rätsels in den Sinn kommt.	
Der Moment eines hart erkämpften Sieges.	
Ein Moment, in dem man ein intensives Gefühl der Gemeinschaft mit einem Mitspieler erlebt.	
Ein Moment der Vervollständigung, welche man angestrebt hat.	

3.5 Was sind Deine Gründe Dich gesund ernähren zu wollen? Gib für jede Aussage an, wie sehr sie auf Dich zutrifft. *Bitte pro Zeile jeweils ein Kästchen ankreuzen!*

	Stimme überhaupt nicht zu						Stimme voll und ganz zu
Weil das Gefühl habe, dass ich Verantwortung für meine eigene Gesundheit übernehmen will.	○	○	○	○	○	○	○
Weil ich mich schuldig fühlen oder mich schämen würde, wenn ich mich nicht gesund ernähre.	○	○	○	○	○	○	○
Weil ich persönlich glaube, dass es das Beste für meine Gesundheit ist.	○	○	○	○	○	○	○
Weil ich andere verärgern würden, wenn ich es nicht täte.	○	○	○	○	○	○	○
Ich denke wirklich nicht darüber nach.	○	○	○	○	○	○	○
Weil ich sorgfältig darüber nachgedacht habe und glaube, dass es für viele Aspekte meines Lebens sehr wichtig ist.	○	○	○	○	○	○	○
Weil ich mich schlecht fühlen würde, wenn ich mich nicht gesund ernähren würde.	○	○	○	○	○	○	○
Weil es eine wichtige Entscheidung ist, die ich unbedingt treffen möchte.	○	○	○	○	○	○	○
Weil ich den Druck von anderen spüre so zu handeln.	○	○	○	○	○	○	○
Weil es leichter ist, das zu tun, was mir gesagt wird, als darüber nachzudenken.	○	○	○	○	○	○	○
Weil es mit meinen Lebenszielen übereinstimmt.	○	○	○	○	○	○	○
Weil ich möchte, dass andere mich akzeptieren.	○	○	○	○	○	○	○
Weil es sehr wichtig ist, möglichst gesund zu sein.	○	○	○	○	○	○	○

Weil ich möchte, dass andere sehen, dass ich es kann.	○	○	○	○	○	○	○
Ich weiß nicht wirklich warum.	○	○	○	○	○	○	○

4. Verhalten

4.1 Wie einfach wäre es für dich eine gesunde Ernährung einzuhalten? Gib für jede Aussage an, wie sehr sie auf Dich zutrifft. *Bitte pro Zeile jeweils ein Kästchen ankreuzen!*

	Stimme überhaupt nicht zu						Stimme voll und ganz zu
Wenn ich wollte, könnte ich einfach in den nächsten zwei Wochen gesund essen.	○	○	○	○	○	○	○
Ich habe Kontrolle darüber, ob ich mich gesund ernähre.	○	○	○	○	○	○	○
Ob ich mich in der nächsten Woche gesund ernähre oder nicht, liegt ganz bei mir.	○	○	○	○	○	○	○
Ich glaube, dass ich die Möglichkeit habe, mich nächste Woche gesund zu ernähren.	○	○	○	○	○	○	○
Ich bin überzeugt davon, dass ich mich in den nächsten zwei Wochen gesund ernähren könnte, wenn ich das möchte.	○	○	○	○	○	○	○

4.2 In den nächsten zwei Wochen gesundes Essen zu essen, wäre für mich:

Beispiel: Mit dieser Beurteilung sagst Du aus, dass Du gesund Essen eher attraktiv (gut) als unattraktiv (nicht gut) findest:

attraktiv	○	⊗	○	○	○	○	○	unattraktiv

Bitte pro Zeile jeweils einmal ein Kästchen ankreuzen!

unwichtig	○	○	○	○	○	○	○	wichtig
unnütz	○	○	○	○	○	○	○	nützlich
minderwertig	○	○	○	○	○	○	○	wertvoll
unerfreulich	○	○	○	○	○	○	○	erfreulich
schädlich	○	○	○	○	○	○	○	vorteilhaft
unangenehm	○	○	○	○	○	○	○	angenehm
gut	○	○	○	○	○	○	○	schlecht

4.3 Was sind Deine Absichten für gesunde Ernährung in den nächsten zwei Wochen? Bitte kreuze für jede Aussage an, wie sehr sie auf Dich zutrifft! *Bitte pro Zeile jeweils einmal ein Kästchen ankreuzen!*

	Stimme überhaupt nicht zu						Stimme voll und ganz zu
Ich habe vor, es in den nächsten zwei Wochen zu vermeiden, Junk-Food und Fast-Food zu essen.	○	○	○	○	○	○	○
Ich habe vor, in den nächsten zwei Wochen mehr Gemüse zu essen.	○	○	○	○	○	○	○
Ich werde versuchen. während der nächsten zwei Wochen nur eine gesunde Menge an Fett zu essen.	○	○	○	○	○	○	○
Ich habe vor, in den nächsten zwei Wochen mehr Früchte zu essen.	○	○	○	○	○	○	○
Ich habe vor, mich in den nächsten zwei Wochen gesund zu ernähren.	○	○	○	○	○	○	○
Ich werde versuchen, mich in den nächsten zwei Wochen gesund zu ernähren.	○	○	○	○	○	○	○
Ich plane, mich in den nächsten zwei Wochen gesund zu ernähren.	○	○	○	○	○	○	○

5. Dein Feedback

5.1 Hast Du noch Anmerkungen? Hattest Du Schwierigkeiten bei bestimmten Fragen? Hier hast Du Platz, Deine spontanen Eindrücke zu äußern. Wir sind für jede Anregung dankbar.

Vielen Dank, dass Du an der Befragung teilgenommen hast.

Dein Studienteam der Technischen Universität München

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Pilotstudie „Fit, Food, Fun" – Interventionsgruppe

- BEFRAGUNG **TEIL 2** (FREITAG) -

[Nachfolgende Seiten werden von den SchülerInnen am Studienort ausgefüllt]

Geschlecht:

__ weiblich

__ männlich

Studien-ID: _____

Liebe Schülerin, lieber Schüler,

in diesem Fragebogen geht es nicht um richtige oder falsche Antworten oder um Noten. Es geht darum, dass Du uns Deine eigene Meinung und Deine eigenen Gedanken mitteilst. Bitte fülle den Fragebogen sorgfältig und vollständig aus. Nimm` Dir Zeit und lies` Dir die Fragen gründlich durch. Sprich` Dich bitte nicht mit Deinem Nachbarn/Deiner Nachbarin ab.
Vielen Dank, dass Du bei unserer Studie mitmachst.

Dein Studienteam der Technischen Universität München

1. Ernährung

1.1 Wenn Du etwas isst, wie wichtig ist es für Dich, dass das Nahrungsmittel gesund ist?
Bitte kreuze die Aussage an, die auf Dich am besten zutrifft! *Nur 1 Antwort ist möglich.*

- ☐ Sehr wichtig
- ☐ Wichtig
- ☐ Eher wichtig
- ☐ Eher unwichtig
- ☐ Unwichtig
- ☐ Völlig unwichtig

1.2 Welche der folgenden Aussage trifft auf Dich zu? *Nur 1 Antwort ist möglich.*

- ☐ Ich achte darauf, mich gesund zu ernähren.
- ☐ Ich achte nicht darauf, mich gesund zu ernähren.

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1.3 In meiner täglichen Ernährung achte ich auf…
Bitte kreuze die Aussagen an, die auf Dich am besten zutreffen! *Mehrere Antworten sind möglich.*

- ☐ Eiweiß
- ☐ Zucker
- ☐ Fett
- ☐ Obst
- ☐ Gemüse
- ☐ Wasser
- ☐ Kalorien
- ☐ Sonstiges: ___________________
- ☐ Keine Antwort trifft zu

1.4 Bitte vervollständige die folgende Ernährungsregel, indem Du die fehlenden Wörter ergänzt. *Pro Freifeld kannst Du ein Wort ergänzen.*

__________wählen: Bei Getreideprodukten wie Brot, Nudeln, Reis und Mehl ist die __________variante die beste Wahl für Deine Gesundheit. Lebensmittel aus__________sättigen länger und enthalten__________Nährstoffe als Weißmehlprodukte.

1.5 Wie häufig isst Du die aufgeführten Nahrungsmittel?

Bitte pro Zeile jeweils einmal ein Kästchen ankreuzen!

Wie häufig isst Du die aufgeführten Nahrungsmittel:	*Skala*	nie	selten	mehrmals pro Monat	mehrmals pro Woche	täglich
1. dunkles Brot oder Brötchen (Vollkorn, Roggen)	A	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
2. Kuchen, Teilchen, Plätzchen	D	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
3. Butter (keine Margarine)	F	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
4. fettarme Margarine	F/H	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
5. Marmelade, Honig	D	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
6. Nussnougat-Cremes	D	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
7. fettarme Wurst	E/H	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
8. „normale“ Wurst	E	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
9. Quark	C	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
10. Joghurt	C	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
11. fettarmer Käse (Light-Käse)	C/H	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
12. „normaler“ Käse	C	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
13. Obst, Früchte	B	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
14. Schokolade, Pralinen, Bonbons	D	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
15. Schokoriegel, süße Pausensnacks	D	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
16. Chips, Salzgebäck, Nüsse	G	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
17. Kartoffeln (Salz-, Pellkartoffeln)	A	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
18. Nudeln	A	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
19. Reis	A	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
20. Gemüse	B	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
21. Salat	B	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5

22. Rindfleisch, Kalbfleisch (Rouladen, Rinderbraten, Kalbsgulasch)	E	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
23. Schweinefleisch (Schweinebraten, Gulasch)	E	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
24. Fisch (Forelle, Karpfen, Fischfilets, Fischstäbchen)	E	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
25. Geflügel, Hühner-Frikassee, Geflügelstäbchen	E	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
26. Hamburger, Big Mac	G	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
27. Pommes frites, Kartoffelecken	G	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
28. Bratwurst, Currywurst, Grillhähnchen	G	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
29. Döner, Gyros u. Ä.	G	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
30. Pizza-, China-Imbiss	G	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
31. Tiefkühl-Pizza, Tiefkühl- oder Mikrowellengerichte, Dosen, Tüten	G	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5

Quelle: Beckert-Zieglschmid, C., Brähler, E. (2007). Der Leipziger Lebensstilfragebogen für Jugendliche (LLfJ). Ein Instrument zur Arbeit mit Jugendlichen. Das Handbuch. Göttingen: Vandenhoeck & Ruprecht.

1.6 Bitte vervollständige die folgende Ernährungsregel, indem Du die fehlenden Wörter ergänzt. *Pro Freifeld kannst Du ein Wort ergänzen.*

__________und Salz einsparen: Mit__________gesüßte Lebensmittel und Getränke sind __________empfehlenswert. Vermeide diese möglichst und setze__________sparsam ein. Spare Salz und reduziere den Anteil salzreicher Lebensmittel.

1.7 Wie häufig trinkst Du die aufgeführten Getränke?

Bitte pro Zeile jeweils einmal ein Kästchen ankreuzen!

Wie häufig trinkst Du die aufgeführten Getränke:	*Skala*	nie	selten	mehrmals pro Monat	mehrmals pro Woche	täglich
34. Vollmilch, Kakao	D	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
35. fettarme Milch	E	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
36. Joghurt- oder Milchgetränke (Erdbeer, Vanille, Schoko...)	D	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
37. Kaffee, schwarzer Tee	C	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
38. Kräutertee, Früchtetee	E	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
39. Cola, Limonade	B	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
40. Light-Cola, Light-Limonade, Light-Fruchtsaft, Wasser mit Geschmack	B	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
41. Fruchtsäfte (Orangensaft, Apfelsaft, …)	D	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
42. Mineralwasser, Wasser	E	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
43. Power-, Energydrinks (Red Bull, Flying Horse)	B	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
44. Bier	A	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
45. Wein, Sekt, Prosecco	A	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
46. Spirituosen (Schnaps, Whisky, Cognac, Korn)	A	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
47. alkoholische Mixgetränke, Cocktails, Alcopops	A	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5

Quelle: Beckert-Zieglschmid, C., Brähler, E. (2007). Der Leipziger Lebensstilfragebogen für Jugendliche (LLfJ). Ein Instrument zur Arbeit mit Jugendlichen. Das Handbuch. Göttingen: Vandenhoeck & Ruprecht.

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1.8 Was steckt hinter dem Begriff „Kalorien“ bzw. was ist ein anderer Begriff für Kalorien? *Nur 1 Antwort ist möglich.*

- ☐ Muskelmasse
- ☐ Energie
- ☐ Hunger
- ☐ Durst
- ☐ Weiß nicht

1.9 Was ist ein anderes Wort für Eiweiß? *Schreibe Deine Antwort ins Kästchen!*

1.10 Bitte vervollständige die folgende Ernährungsregel, indem Du die fehlenden Wörter ergänzt. *Pro Freifeld kannst Du ein Wort ergänzen.*

Gesundheitsfördernde Fette nutzen: Bevorzuge__________Öle wie Rapsöl und daraus hergestellte Streichfette. Vermeide__________Fette. Fett steckt oft „unsichtbar“ in verarbeiteten Lebensmitteln wie__________, Gebäck, Süßwaren, Fast-Food und__________.

1.11 Ist Zucker ein Kohlenhydrat? *Nur 1 Antwort ist möglich.*

- ☐ Ja
- ☐ Nein
- ☐ Weiß nicht

1.12 Wie viele Portionen Obst und Gemüse sollte man täglich essen (eine Portion = eine Handvoll)? *Nur 1 Antwort ist möglich.*

- ☐ 0 Portionen
- ☐ 1-2 Portionen
- ☐ 5 Portionen
- ☐ So viele Portionen wie man möchte
- ☐ Weiß nicht

1.13 Welche der folgenden Aussagen ist richtig? *Nur 1 Antwort ist möglich.*

In der täglichen Ernährung sollte man…

- ☐ Zucker einsparen, Salz hingegen darf man so viel essen wie man möchte.
- ☐ Salz einsparen, Zucker hingegen darf man so viel essen wie man möchte.
- ☐ Weder Salz noch Zucker einsparen.
- ☐ Zucker und Salz einsparen.
- ☐ Weiß nicht

1.14 Bitte vervollständige die folgende Ernährungsregel, indem Du die fehlenden Wörter ergänzt. *Pro Freifeld kannst Du ein Wort ergänzen.*

Auf das Gewicht achten und in__________bleiben: Vollwertige__________und körperliche__________gehören zusammen. Dabei ist nicht nur regelmäßiger Sport hilfreich, sondern auch ein aktiver Alltag. Pro Tag 30 bis__________Minuten moderate körperliche Aktivität fördert Deine Gesundheit.

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1.15 Stell Dir vor, Du bist in einer Bäckerei und möchtest ein Brot kaufen. Es gibt ein weißes Brot (aus Weißmehl) und ein dunkles Brot (aus Vollkornmehl). Beide Brote haben den gleichen Preis und sehen lecker aus. Welches Brot würdest Du kaufen?

Nur 1 Antwort ist möglich.

- ☐ Dunkles Brot (aus Vollkornmehl)
- ☐ Weißes Brot (aus Weißmehl)
- ☐ Ich esse kein Brot.

1.16 Welche der folgenden Aussagen ist richtig? *Nur 1 Antwort ist möglich.*

- ☐ Vollkornbrot enthält mehr Nährstoffe (z.B. Ballaststoffe) als Weißbrot UND sättigt mehr als Weißbrot.
- ☐ Weißbrot enthält mehr Nährstoffe (z.B. Ballaststoffe) als Vollkornbrot.
- ☐ Weißbrot und Vollkornbrot unterscheiden sich hinsichtlich der Nährstoffe (z.B. Ballaststoffe) UND der Sättigung nicht.
- ☐ Weiß nicht

1.17 Welches der folgenden Lebensmittel hat bei gleicher Menge den höchsten Fettgehalt? *Nur 1 Antwort ist möglich.*

- ☐ Schokolade
- ☐ Hartkaramellen/Bonbons
- ☐ Gummibärchen
- ☐ Müsli-Riegel
- ☐ Marshmallows
- ☐ Weiß nicht

1.18 Welche der folgenden Aussagen ist richtig? *Nur 1 Antwort ist möglich.*

- ☐ Obst und Gemüse enthalten bei gleicher Menge gleich viel Zucker.
- ☐ Gemüse enthält bei gleicher Menge weniger Zucker als Obst.
- ☐ Obst enthält bei gleicher Menge weniger Zucker als Gemüse.
- ☐ Weiß nicht

1.19 Bitte vervollständige die folgende Ernährungsregel, indem Du die fehlenden Wörter ergänzt. *Pro Freifeld kannst Du ein Wort ergänzen.*

Am besten__________trinken: Trinke rund_____Liter jeden Tag. Am besten__________oder andere kalorienfreie Getränke wie ungesüßten Tee. Zuckergesüßte und alkoholische Getränke sind__________empfehlenswert.

1.20 Welches der folgenden Lebensmittel hat bei gleicher Menge den höchsten Zuckergehalt? *Nur 1 Antwort ist möglich.*

- ☐ Softdrinks (z.B. Limonade, Cola)
- ☐ Wasser
- ☐ Kuhmilch
- ☐ Saftschorle
- ☐ Tomatensaft
- ☐ Weiß nicht

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1.21 Welche der folgenden Aussagen ist richtig? *Nur 1 Antwort ist möglich.*

Eiweiß ist besonders viel enthalten in…

- ☐ Butterschmalz
- ☐ Gurke
- ☐ Pizza
- ☐ Lakritze
- ☐ Thunfisch
- ☐ Weiß nicht

1.22 Bitte vervollständige die folgende Ernährungsregel, indem Du die fehlenden Wörter ergänzt. *Pro Freifeld kannst Du ein Wort ergänzen.*

Gemüse und__________– nimm „5 am Tag“: Genieße mindestens_____Portionen Gemüse und_____Portionen__________am Tag.

1.23 Für was steht die Abkürzung DGE? *Nur 1 Antwort ist möglich.*

- ☐ Deutsche Genossenschaft für Ernährung
- ☐ Deutsche Gesellschaft für Erderwärmung
- ☐ Deutsche Gesellschaft für Ernährungsweisen
- ☐ Deutsche Gesellschaft für Ernährung
- ☐ Weiß nicht

2. Sport

2.1 Wie oft machst Du im Winter in der Woche Sport? *Nur 1 Antwort ist möglich.*

☐ Regelmäßig mehr als 2 Stunden
☐ Regelmäßig 1 bis 2 Stunden
☐ Regelmäßig weniger als 1 Stunde
☐ Keine sportliche Betätigung

2.2 Wie oft machst Du im Sommer in der Woche Sport? *Nur 1 Antwort ist möglich.*

☐ Regelmäßig mehr als 2 Stunden
☐ Regelmäßig 1 bis 2 Stunden
☐ Regelmäßig Weniger als 1 Stunde
☐ Keine sportliche Betätigung

2.3 Wie viele Kalorien [kcal] verbrauchst Du ungefähr, wenn Du 2 Stunden bei mittlerer Anstrengung Fahrrad fährst? *Nur 1 Antwort ist möglich.*

☐ Weniger als 200 kcal
☐ 600 – 1000 kcal
☐ Mehr als 1000 kcal
☐ Weiß nicht

2.4 Bei welcher der folgenden drei Sportarten verbrauchst Du bei gleicher Durchführung (z.B. Dauer, Strecke) die meiste Energie? *Nur 1 Antwort ist möglich.*

☐ Radfahren
☐ Laufen/Jogging
☐ Schwimmen
☐ Weiß nicht

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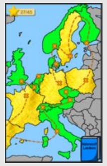
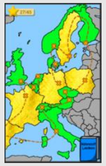
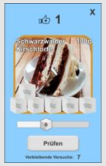
3. Erlebnis

3.1 Wie haben Dir folgende Spielelemente gefallen? *Bitte pro Zeile jeweils einmal ein Kästchen ankreuzen!*

		Ich hasse es	Ich mag es nicht	Es ist okay	Ich mag es	Ich liebe es	Ich kenne das Spielelement nicht
	Europareise	○	○	○	○	○	○
	Nährstoff Quiz	○	○	○	○	○	○
	Schätzspiel	○	○	○	○	○	○
	Rucksackspiel	○	○	○	○	○	○
	Nährstoff-Lexikon	○	○	○	○	○	○

3.2 Wie viel hast Du durch die folgenden Spielelemente gelernt? *Bitte pro Zeile jeweils einmal ein Kästchen ankreuzen!*

		Ich habe nichts gelernt	Ich habe wenig gelernt	Ich habe einiges gelernt	Ich habe viel gelernt	Ich kenne das Spielelement nicht
	Europareise	○	○	○	○	○
	Nährstoff Quiz	○	○	○	○	○
	Schätzspiel	○	○	○	○	○
	Rucksackspiel	○	○	○	○	○
	Nährstoff-Lexikon	○	○	○	○	○

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3.3 Wie sehr stimmst Du den folgenden Aussagen zu? Gib für jede Aussage an, wie sehr sie auf Dich zutrifft. *Bitte pro Zeile jeweils einmal ein Kästchen ankreuzen!*

	Trifft überhaupt nicht zu	Trifft eher nicht zu	Weder noch	Eher zutreffend	Trifft voll und ganz zu
Fit Food Fun würde es mir ermöglichen mehr über Ernährung zu lernen.	○	○	○	○	○
Fit Food Fun würde meine Ernährung verbessern.	○	○	○	○	○
Fit Food Fun würde es mir erleichtern mich gesund zu ernähren.	○	○	○	○	○
Ich würde Fit Food Fun als nützliches Hilfsmittel für eine gesunde Ernährung ansehen.	○	○	○	○	○
Ich würde Fit Food Fun in meiner Freizeit weiterspielen.	○	○	○	○	○
Ich würde Fit Food Fun meinen Freunden empfehlen.	○	○	○	○	○

3.4 Würdest Du Fit Food Fun kaufen, wenn es im Store verfügbar ist? *Nur 1 Antwort ist möglich.*

☐ Ja
☐ Nein

3.5 Für welchen Preis würdest Du Fit Food Fun kaufen, wenn es im Store verfügbar ist? *Nur 1 Antwort ist möglich.*

☐ Ich würde es nicht kaufen
☐ Kostenlos
☐ Weniger als €2
☐ €2 - €5
☐ €6 - €10
☐ Mehr als €10

3.6 Wie sehr stimmst Du den folgenden Aussagen über das Spiel zu? Gib für jede Aussage an, wie sehr sie auf Dich zutrifft. *Bitte pro Zeile jeweils einmal ein Kästchen ankreuzen!*

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Weder noch	Stimme zu	Stimme voll und ganz zu
Ich denke, dass ich das Spiel gerne häufig benutzen würde.	○	○	○	○	○
Ich fand das Spiel unnötig komplex (kompliziert).	○	○	○	○	○
Ich fand das Spiel einfach zu benutzen.	○	○	○	○	○
Ich glaube, ich würde die Hilfe einer technisch versierten (fitten) Person benötigen, um das Spiel benutzen zu können.	○	○	○	○	○
Ich fand, die verschiedenen Funktionen in diesem Spiel waren gut integriert (zusammengefügt).	○	○	○	○	○
Ich denke, das Spiel enthielt zu viele Inkonsistenzen (Ungereimtheiten).	○	○	○	○	○
Ich kann mir vorstellen, dass die meisten Menschen den Umgang mit diesem Spiel sehr schnell lernen.	○	○	○	○	○
Ich fand das Spiel sehr umständlich zu nutzen.	○	○	○	○	○
Ich fühlte mich bei der Benutzung des Spiels sehr sicher.	○	○	○	○	○
Ich musste eine Menge lernen, bevor ich anfangen konnte das Spiel zu verwenden.	○	○	○	○	○

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3.7 Bitte kreuze an, wie du das Fit Food Fun Spiel eher findest! *Beispiel: Mit dieser Beurteilung sagst Du aus, dass Du das Spiel eher attraktiv (gut) als unattraktiv (nicht gut) findest:*

attraktiv	○	⊗	○	○	○	○	○	unattraktiv

Bitte pro Zeile jeweils einmal ein Kästchen ankreuzen!

unerfreulich	○	○	○	○	○	○	○	erfreulich
unverständlich	○	○	○	○	○	○	○	verständlich
kreativ	○	○	○	○	○	○	○	phantasielos
leicht zu lernen	○	○	○	○	○	○	○	schwer zu lernen
wertvoll	○	○	○	○	○	○	○	minderwertig
langweilig	○	○	○	○	○	○	○	spannend
uninteressant	○	○	○	○	○	○	○	interessant
unberechenbar	○	○	○	○	○	○	○	voraussagbar
schnell	○	○	○	○	○	○	○	langsam
originell	○	○	○	○	○	○	○	konventionell
behindernd	○	○	○	○	○	○	○	unterstützend
gut	○	○	○	○	○	○	○	schlecht
kompliziert	○	○	○	○	○	○	○	einfach
abstoßend	○	○	○	○	○	○	○	anziehend
herkömmlich	○	○	○	○	○	○	○	neuartig
unangenehm	○	○	○	○	○	○	○	angenehm
sicher	○	○	○	○	○	○	○	unsicher
aktivierend	○	○	○	○	○	○	○	einschläfernd
erwartungskonform	○	○	○	○	○	○	○	nicht erwartungskonform
ineffizient	○	○	○	○	○	○	○	effizient
übersichtlich	○	○	○	○	○	○	○	verwirrend
unpragmatisch	○	○	○	○	○	○	○	pragmatisch
aufgeräumt	○	○	○	○	○	○	○	überladen
attraktiv	○	○	○	○	○	○	○	unattraktiv
sympathisch	○	○	○	○	○	○	○	unsympathisch
konservativ	○	○	○	○	○	○	○	innovativ

3.8 Wie hast Du Dich beim Spielen gefühlt? Gib für jede Aussage an, wie sehr sie auf Dich zutrifft. *Bitte pro Zeile jeweils einmal ein Kästchen ankreuzen!*

	Stimme überhaupt nicht zu						Stimme voll und ganz zu
Während ich das Spiel spielte, dachte ich darüber nach, wie sehr es mir gefällt.	○	○	○	○	○	○	○
Ich war überhaupt nicht nervös wegen des Spiels.	○	○	○	○	○	○	○
Ich hatte das Gefühl, dass es meine Entscheidung war, dieses Spiel zu spielen.	○	○	○	○	○	○	○
Ich denke ich bin ziemlich gut in diesem Spiel.	○	○	○	○	○	○	○
Ich fand das Spiel sehr interessant.	○	○	○	○	○	○	○
Ich fühlte mich angespannt, während ich das Spiel spielte.	○	○	○	○	○	○	○
Ich denke, dass ich mich bei diesem Spiel im Vergleich zu anderen Schülern ziemlich gut geschlagen habe.	○	○	○	○	○	○	○
Das Spiel zu spielen hat Spaß gemacht.	○	○	○	○	○	○	○
Ich fühlte mich entspannt, während ich das Spiel spielte.	○	○	○	○	○	○	○
Ich habe das Spiel sehr gerne gespielt.	○	○	○	○	○	○	○
Ich hatte nicht wirklich die Wahl, ob ich das Spiel spielen möchte oder nicht.	○	○	○	○	○	○	○
Ich bin mit meiner Leistung in diesem Spiel zufrieden.	○	○	○	○	○	○	○
Ich war besorgt, während ich das Spiel spielte.	○	○	○	○	○	○	○
Ich fand das Spiel sehr langweilig.	○	○	○	○	○	○	○
Ich hatte das Gefühl, das zu tun, was ich will, während ich das Spiel spielte.	○	○	○	○	○	○	○
Ich fühlte mich ziemlich gut in diesem Spiel.	○	○	○	○	○	○	○
Ich dachte das Spiel war sehr interessant.	○	○	○	○	○	○	○
Ich fühlte mich unter Druck gesetzt, während ich das Spiel spielte.	○	○	○	○	○	○	○
Ich fühlte mich, als müsste ich das Spiel spielen.	○	○	○	○	○	○	○
Ich würde das Spiel als sehr unterhaltsam bezeichnen	○	○	○	○	○	○	○
Ich habe das Spiel gespielt, weil ich keine andere Wahl hatte.	○	○	○	○	○	○	○
Nachdem ich eine Weile dieses Spiel gespielt hatte, fühlte ich mich ziemlich kompetent.	○	○	○	○	○	○	○

4. Verhalten

4.1 Wie einfach wäre es für dich eine gesunde Ernährung einzuhalten? Gib für jede Aussage an, wie sehr sie auf Dich zutrifft. *Bitte pro Zeile jeweils ein Kästchen ankreuzen!*

	Stimme überhaupt nicht zu						Stimme voll und ganz zu
Wenn ich wollte, könnte ich einfach in den nächsten zwei Wochen gesund essen.	○	○	○	○	○	○	○
Ich habe Kontrolle darüber, ob ich mich gesund ernähre.	○	○	○	○	○	○	○
Ob ich mich in der nächsten Woche gesund ernähre oder nicht, liegt ganz bei mir.	○	○	○	○	○	○	○
Ich glaube, dass ich die Möglichkeit habe, mich nächste Woche gesund zu ernähren.	○	○	○	○	○	○	○
Ich bin überzeugt davon, dass ich mich in den nächsten zwei Wochen gesund ernähren könnte, wenn ich das möchte.	○	○	○	○	○	○	○

4.2 In den nächsten zwei Wochen gesundes Essen zu essen, wäre für mich:

Beispiel: Mit dieser Beurteilung sagst Du aus, dass Du gesund Essen eher attraktiv (gut) als unattraktiv (nicht gut) findest:

attraktiv	○	⊗	○	○	○	○	○	unattraktiv

Bitte pro Zeile jeweils einmal ein Kästchen ankreuzen!

unwichtig	○	○	○	○	○	○	○	wichtig
unnütz	○	○	○	○	○	○	○	nützlich
minderwertig	○	○	○	○	○	○	○	wertvoll
unerfreulich	○	○	○	○	○	○	○	erfreulich
schädlich	○	○	○	○	○	○	○	vorteilhaft
unangenehm	○	○	○	○	○	○	○	angenehm
gut	○	○	○	○	○	○	○	schlecht

4.3 Was sind Deine Absichten für gesunde Ernährung in den nächsten zwei Wochen? Bitte kreuze für jede Aussage an, wie sehr sie auf Dich zutrifft! *Bitte pro Zeile jeweils einmal ein Kästchen ankreuzen!*

	Stimme überhaupt nicht zu						Stimme voll und ganz zu
Ich habe vor, es in den nächsten zwei Wochen zu vermeiden, Junk-Food und Fast-Food zu essen.	○	○	○	○	○	○	○
Ich habe vor, in den nächsten zwei Wochen mehr Gemüse zu essen.	○	○	○	○	○	○	○
Ich werde versuchen. während der nächsten zwei Wochen nur eine gesunde Menge an Fett zu essen.	○	○	○	○	○	○	○
Ich habe vor, in den nächsten zwei Wochen mehr Früchte zu essen.	○	○	○	○	○	○	○
Ich habe vor, mich in den nächsten zwei Wochen gesund zu ernähren.	○	○	○	○	○	○	○
Ich werde versuchen, mich in den nächsten zwei Wochen gesund zu ernähren.	○	○	○	○	○	○	○
Ich plane, mich in den nächsten zwei Wochen gesund zu ernähren.	○	○	○	○	○	○	○

5. Dein Feedback

5.1 Hast Du noch Anmerkungen? Hattest Du Schwierigkeiten bei bestimmten Fragen? Hier hast Du Platz, Deine spontanen Eindrücke zu äußern. Wir sind für jede Anregung dankbar.

Vielen Dank, dass Du an der Befragung teilgenommen hast.

Dein Studienteam der Technischen Universität München

E

QUESTIONNAIRES OF NUTRILIZE PILOT STUDY

These are the two screening questionnaires and the post-study questionnaire of the pilot study on *Nutrilize*. The Norman, Baecke, and FFQ survey are provided in their German equivalent version in Appendix G.

Teil A:

A1. **Stimmen Sie zu, dass Ihre Daten aus den zwei Screening Fragebögen für Studienzwecke genutzt werden dürfen?**

- Ja ☐
- Nein ☐

Teil B:

B1. **Alter:**

- Jünger als 18 Jahre ☐
- 18 ☐
- 19 ☐
- 20 ☐
- 21 ☐
- 22 ☐
- 23 ☐
- 24 ☐
- 25 ☐
- 26 ☐
- 27 ☐
- 28 ☐
- 29 ☐
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71 ☐

72 ☐

73 ☐

74 ☐

75 ☐

76 ☐

77 ☐

78 ☐

79 ☐

80 ☐

Älter als 80 Jahre ☐

B2. Geschlecht:

weiblich ☐

männlich ☐

B3. Größe (cm):

B4. Gewicht (kg):

Teil C:

Ihr BMI ist: {round(BMIeq,2)}

C1. {Grosse/100}

C2. {Gewicht/(Grose*Grose)}

C4. Ist Ihr BMI weniger als 25 oder größer als 40?

Ja ☐

Nein ☐

Teil D:

D1. Sind Sie schwanger, stillen Sie oder planen Sie in den kommenden Monaten schwanger zu werden?

Ja ☐

Nein ☐

D2. Haben Sie von Ihrem Arzt die Anordnung erhalten, aus gesundheitlichen Gründen (z.B. Diabetes, Zöliakie, chronische Erkrankungen), Diät zu halten?

Ja ☐

Nein ☐

D3. Erhalten Sie von einem Ernährungsberater derzeit einen Diätplan?

Ja ☐

Nein ☐

D4. Leiden Sie an einer Nahrungsintoleranz oder einer Nahrungsmittelallergie?

Ja ☐

Nein ☐

D5. Wenn ja, welche?

D6. Leiden Sie an einer der folgenden Erkrankungen?

	Ja	Nein
Bluterkrankheit	☐	☐
Alkoholabhängigkeit	☐	☐
Drogenabhängigkeit	☐	☐
Depression	☐	☐
Erkrankungen, welche die Nährstoffresorption, Verdauungsfunktion, Verstoffwechselung oder Ausscheidung betreffen	☐	☐

D7. Haben Sie eine Internet flatrate?

Ja ☐

Nein ☐

D8. **Besitzen Sie ein Android Smartphone?**

Ja ☐

Nein ☐

D9. **Haben Sie Zugang zu einer Körperwaage?**

Ja ☐

Nein ☐

D10. **Nehmen Sie regelmäßig Medikamente ein (Ausnahme: orale Kontrazeptiva)?**

Ja ☐

Nein ☐

D11. **Wenn ja, welche und warum?**

Teil E:

Leiden Sie an einer der folgenden Erkrankungen oder wurde einer der folgenden Erkrankungen bei Ihnen schon einmal diagnostiziert?

E1. **Krebs (innerhalb der letzten 3 Jahre)**

Ja ☐

Nein ☐

E2. **Wenn ja, sind Sie in ärztlicher Behandlung?**

Ja ☐

Nein ☐

E3. **Um welche Krebsform handelt es sich?**

E4. **Hypertonie (hoher Blutdruck)**

Ja ☐

Nein ☐

E5. **Wenn ja, sind Sie in ärztlicher Behandlung?**

Ja ☐

Nein ☐

E6. **Allergien**

Ja ☐

Nein ☐

E7. **Wenn ja, sind Sie in ärztlicher Behandlung?**

Ja ☐

Nein ☐

E8. **Um welche Allergien handelt es sich dabei?**

E9. **Chronische Erkrankungen (z.B. Diabetes, Leber-, Nieren-, Lungen-, Herzerkrankungen, Schilddrüsenerkrankungen, Anämie)**

Ja ☐

Nein ☐

E10. **Wenn ja, sind Sie in ärztlicher Behandlung?**

Ja ☐

Nein ☐

E11. **Um welche Erkrankung(en) handelt es sich?**

Teil F:

F1. **Leiden Sie an einer Erkrankung, die in der Auflistung zu Frage 3 nicht genannt wurde?**

Ja ☐

Nein ☐

F2. **Wenn ja, welche?**

F3. **Haben Sie andere Beschwerden, die Ihre körperliche Aktivität beeinflussen?**

Ja ☐

Nein ☐

F4. **Wenn ja, welche?**

Willkommen zum Screening fragebogen2

Teil A: Teilnehmerdaten

A1. **Bitte geben Sie hier Ihren persönlichen Tokencode ein, der beim 1. Screening für Sie generiert wurde:**

A2. **Ethnische Zugehörigkeit**

- Kaukasisch ☐
- Asiatisch ☐
- Schwarzafrikanisch ☐
- Sonstiges ☐

Sonstiges

A3. **Beruf:**

A4. **Berufsstand:**

- Vollzeit ☐
- Teilzeit ☐

A5. **Höchster beruflicher Ausbildungsabschluss:**

- Hochschulabschluss ☐
- Fachhochschulabschluss (auch Ingenieurschulabschluss) ☐
- Abschluss einer Ausbildung an einer Fach-, Meister-, Technikerschule, Berufs- oder Fachakademie ☐
- Abschluss einer beruflichen Ausbildung (Lehre) oder gleichwertiger Berufsfachschulabschluss ☐
- Sonstiger beruflicher Abschluss (z.B. Anlernberuf, berufliches Praktikum) ☐
- Noch in beruflicher Ausbildung, Student(in) ☐
- Kein beruflicher Abschluss und nicht in beruflicher Ausbildung, Schüler(in) ☐

Teil B: Informationen zum Rauchen

B1. **Sind Sie Raucher?**

- Ja ☐
- Nein ☐

B2. **Wenn ja, seit wie vielen Monaten/Jahren sind Sie Raucher?**

B3. **Wie viele Zigaretten, Zigarren, Pfeifen rauchen Sie täglich?**

- weniger als 5 ☐
- 5-10 ☐
- 10-15 ☐
- mehr als 15 ☐

B4. **Wenn nein, sind Sie ein ehemaliger Raucher?**

- Nein, ich habe noch nie geraucht. ☐
- Ja, ich habe vor über einem Jahr mit dem Rauchen aufgehört. ☐
- Ja, ich habe innerhalb des letzten Jahres mit dem Rauchen aufgehört. ☐

Teil C: Essgewohnheiten

C1. **Halten Sie eine spezielle Diät aus persönlichen oder religiösen Gründen ein?**

- Ja ☐
- Nein ☐

C2. **Wenn ja, auf welche Lebensmittel verzichten Sie?**

C3. **Wie oft essen Sie Ihre Hauptmahlzeit außer Haus?**

- Niemals oder bis zu einmal im Monat ☐
- 2-3mal im Monat ☐
- 1mal in der Woche ☐
- 2 bis mehrmals in der Woche ☐

C4. Wie oft bereiten Sie Ihr Essen frisch zu?

- jeden Tag ☐
- 4-6mal in der Woche ☐
- 1-3mal in der Woche ☐
- (fast) nie ☐

C5. Wie viele warme Gerichte essen Sie am Tag?

- niemals oder selten ☐
- 1mal ☐
- 2mal ☐
- 3 oder mehr ☐

C6. Welcher Faktor ist entscheidend, wenn Sie ein Rezpt aussuchen ?

- Zubereitungszeit ☐
- Anzahl der Zutaten ☐
- Aufwand (Schwierigkeitsgrad) ☐

C7. Wie viel Zeit verbringen Sie im Durchschnitt mit der Zubereitung einer Hauptmahlzeit?

- weniger als 10 Minuten ☐
- 10-20 Minuten ☐
- 20-30 Minuten ☐
- bis zu 1 Stunde ☐
- über 1 Stunde ☐

C8. Wie oft ersetzen Sie Ihre Hauptmahlzeiten durch Zwischenmahlzeiten (Snacks)?

- jeden Tag ☐
- 4-6mal in der Woche ☐
- 1-3mal in der Woche ☐
- (fast) nie ☐

Teil D: Wie fühlen Sie sich?

D1. Ich fühle mich gesund.

- trifft überhaupt nicht zu ☐
- trifft weniger zu ☐
- weder noch ☐
- trifft überwiegend zu ☐
- trifft vollständig zu ☐

D2. Ich achte auf meine Gesundheit.

- trifft überhaupt nicht zu ☐
- trifft weniger zu ☐
- weder noch ☐
- trifft überwiegend zu ☐
- trifft vollständig zu ☐

D3. Ich tue viel für meine Gesundheit.

- trifft überhaupt nicht zu ☐
- trifft weniger zu ☐
- weder noch ☐
- trifft überwiegend zu ☐
- trifft vollständig zu ☐

D4. Mich um die Verbesserung meiner Gesundheit zu bemühen, halte ich für Zeitverschwendung.

- trifft überhaupt nicht zu ☐
- trifft weniger zu ☐
- weder noch ☐
- trifft überwiegend zu ☐
- trifft vollständig zu ☐

D5. **Von all der Aufmerksamkeit, die um Gesundheit und Krankheitsprävention betrieben wird, fühle ich mich gelangweilt.**

- trifft überhaupt nicht zu ☐
- trifft weniger zu ☐
- weder noch ☐
- trifft überwiegend zu ☐
- trifft vollständig zu ☐

D6. **Der einzige Sinn, mich um meine Gesundheit zu kümmern, ist der, ein möglichst hohes Lebensalter zu erreichen.**

- trifft überhaupt nicht zu ☐
- trifft weniger zu ☐
- weder noch ☐
- trifft überwiegend zu ☐
- trifft vollständig zu ☐

D7. **Ich ernähre mich häufig gesund.**

- trifft überhaupt nicht zu ☐
- trifft weniger zu ☐
- weder noch ☐
- trifft überwiegend zu ☐
- trifft vollständig zu ☐

D8. **Ich fühle mich unwohl, wenn ich mich ungesund ernähre.**

- trifft überhaupt nicht zu ☐
- trifft weniger zu ☐
- weder noch ☐
- trifft überwiegend zu ☐
- trifft vollständig zu ☐

D9. **Weil ich es für selbstverständlich halte, brauche ich nicht darüber nachzudenken, mich gesund zu ernähren.**

- trifft überhaupt nicht zu ☐
- trifft weniger zu ☐
- weder noch ☐
- trifft überwiegend zu ☐
- trifft vollständig zu ☐

Teil E: Wie sicher sind Sie?

Wie sicher sind Sie, die folgenden Situationen zu bewältigen:

Ich schaffe es, eine gesunde Ernährungsweise beizubehalten...

E1. **...auch wenn ich eine längere Zeit bräuchte, um mich daran zu gewöhnen**

- sehr unsicher ☐
- eher unsicher ☐
- eher sicher ☐
- sehr sicher ☐

E2. **…auch wenn ich es mehrmals versuchen müsste, bis es funktioniert**

- sehr unsicher ☐
- eher unsicher ☐
- eher sicher ☐
- sehr sicher ☐

E3. **…auch wenn ich meine ganze Ernährungsweise neu überdenken müsste**

- sehr unsicher ☐
- eher unsicher ☐
- eher sicher ☐
- sehr sicher ☐

E4. **…auch wenn ich nicht viel von anderen unterstützt würde**

- sehr unsicher ☐
- eher unsicher ☐
- eher sicher ☐
- sehr sicher ☐

E5. **…auch wenn ich einen genauen Ernährungsplan einzuhalten hätte**

- sehr unsicher ☐
- eher unsicher ☐
- eher sicher ☐
- sehr sicher ☐

Teil F: Fragen zur Technik- und Gadget-Affinität

F1. **Ich liebe es, neue elektronische Geräte zu besitzen.**

- trifft überhaupt nicht zu ☐
- trifft weniger zu ☐
- weder noch ☐
- trifft überwiegend zu ☐
- trifft vollständig zu ☐

F2. **Es macht mir Spaß, ein elektronisches Gerät auszuprobieren.**

- trifft überhaupt nicht zu ☐
- trifft weniger zu ☐
- weder noch ☐
- trifft überwiegend zu ☐
- trifft vollständig zu ☐

F3. **Es fällt mir leicht, die Bedienung eines elektronischen Geräts zu lernen.**

- trifft überhaupt nicht zu ☐
- trifft weniger zu ☐
- weder noch ☐
- trifft überwiegend zu ☐
- trifft vollständig zu ☐

F4. **Elektronische Geräte erleichtern mir den Alltag.**

- trifft überhaupt nicht zu ☐
- trifft weniger zu ☐
- weder noch ☐
- trifft überwiegend zu ☐
- trifft vollständig zu ☐

F5. **Elektronische Geräte helfen, mich selbst besser kennenzulernen**

- trifft überhaupt nicht zu ☐
- trifft weniger zu ☐
- weder noch ☐
- trifft überwiegend zu ☐
- trifft vollständig zu ☐

F6. **Elektronische Geräte verursachen Stress.**

- trifft überhaupt nicht zu ☐
- trifft weniger zu ☐
- weder noch ☐
- trifft überwiegend zu ☐
- trifft vollständig zu ☐

F7. **Elektronische Geräte machen vieles umständlicher.**

- trifft überhaupt nicht zu ☐
- trifft weniger zu ☐
- weder noch ☐
- trifft überwiegend zu ☐
- trifft vollständig zu ☐

F8. **Elektronische Geräte sammeln zu viele persönliche Daten.**

- trifft überhaupt nicht zu ☐
- trifft weniger zu ☐
- weder noch ☐
- trifft überwiegend zu ☐
- trifft vollständig zu ☐

F9. **Wie häufig benutzen sie ein oder mehrere smart Gadgets zur Selbstmessung (z.B. Smartphone, Aktivitätstracker: JawBone, FitBit usw., Smartwaage)?**

- nie ☐
- selten ☐
- gelegentlich ☐
- oft ☐
- laufend ☐

F10. **Welche Smartgadgets benutzen Sie zur Selbstmessung?**

(eg. Smartphone: Samsung S6)

Smartphone: ____________________

Aktivitätstracker: ____________________

Smartwatch: ____________________

Smartwaage: ____________________

Pulsmesser: ____________________

Schlaftracker: ____________________

Sonstiges: ____________________

F11. **Welche Gesundheitsdaten sammeln Sie bereits regelmäßig von sich?**

Bewegung/Sport: ____________________

Essenseinnahme: ____________________

Trinkmenge: ____________________

Gewicht: ____________________

Körperfettanteil: ____________________

Puls: ____________________

Schlaf: ____________________

Sonstiges: ____________________

Bitte kontaktieren Sie Ihr Studienzentrum per E-Mail, wenn folgenden Situationen auftreten:

Wenn Sie krank werden oder verschreibungspflichtige Medikamente während der Studie einnehmen Wenn Sie Ihre Ernährung umstellen, abweichend von den Empfehlungen, die Sie von unserem Studienzentrum erhalten haben Wenn Sie schwanger werden Wenn sich Ihre Post- oder E-Mail-Adresse während der Studie ändert

Teil A: Question Group 1

A1. **Bitte geben Sie hier Ihren persönlichen Tokencode ein, der beim 1. Screening für Sie generiert wurde:**

A2. **Die Nutrilize Webseite war einfach zu benutzen.**

- Ja
- Nein
- Habe ich nicht benutzt

A3. **Haben Sie Verbesserungsvorschläge für die Webseite?**

A4. **Haben Sie die Webseite genutzt, um sich während der Studie zu informieren?**

- Oft
- Selten
- Nie

A5. **Wenn ja, welche haben Sie benutzt?**

A6. **Die Anleitungen für jeden Teil des Projekts waren einfach zu folgen.**

- Ja
- Nein
- Teil /Teils

A7. **Falls nicht, welche Anleitung(en) und warum war(en) sie nicht zu verstehen?**

A8. **Die Anzahl der Aufgaben, die Sie an Ihren Messtagen erledigen mussten (z.B. Blutabnahme, Körpermessungen) waren...**

- Viel zu viel
- Ein bisschen zu viel
- Viel zu wenig
- Ein bisschen zu wenig
- Akzeptabel

A9. **Die Anzahl der Fragebögen, die Sie während der Studie ausfüllen mussten, waren ...**

- Viel zu viel
- Ein bisschen zu viel
- Akzeptabel
- Viel zu wenig
- Ein bisschen zu wenig

A10. **Ich habe den Ernährungshäufigkeitsfragebogen (FFQ) verstanden.**

- Ja
- Nein
- Teils/Teils

A11. **Wenn nicht, was war nicht zu verstehen?**

A12. **Ich habe den Aktivitätsfragebogen (Baecke) verstanden.**

- Ja
- Nein
- Teils/Teils

A13. **Wenn nicht, was war nicht zu verstehen?**

A14. **Haben im Ernährungshäufigkeitsfragebogen (FFQ) Lebensmittel, die Sie regelmäßig konsumieren, gefehlt?**

- Ja
- Nein

A15. **Falls ja, welche Lebensmittel haben gefehlt?**

A16. Welche Angebote der App haben Ihnen gefallen? (Mehrfachwahl).

- Visualisierung auf dem Home Screen (Screen 1) ☐
- Rezeptempfehlungen (Screen 2) ☐
- Tagebuch Eingabe (Screen 3) ☐
- Tagebuchübersicht ☐
- Statistische Übersicht (Screen 4) ☐
- Übersicht des Nährstoffstatus (Screen 5) ☐
- Widget (Screen 6) ☐
- Gadget Anbindung (Screen 7) ☐
- Notifications ☐
- „Mein persönliches Ziel“ ☐
- Präferenzeingabe (Screen 8) ☐

A17. Das Ernährungsfeedback der App war für meine alltägliche Ernährung hilfreich.

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A18. Falls unzutreffend, warum?

A19. Das Ernährungstagebuch war einfach zu benutzen.

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A20. Falls unzutreffend, warum?

A21. Wie oft haben Sie Ihre Mahlzeiten in das Ernährungstagebuch eingetragen?

- Mehrmals am Tag ☐
- Einmal pro Tag ☐
- Mehrmals pro Woche ☐
- Einmal pro Woche ☐
- Seltener als 1 mal pro Woche ☐

A22. Falls selten, warum?

A23. Wenn Sie die Wahl hätten, würden Sie lieber das Ernährungstagebuch ausfüllen oder einen wöchentlichen Fragebogen, der Ihren Lebensmittelverzehr der letzten Woche in ein paar Fragen abfragt?

- Lieber Ernährungstagebuch ☐
- Lieber wöchentlichen Fragebogen ☐

A24. Haben Sie die Empfehlungen umgesetzt, die Sie bekommen haben?

- Immer ☐
- Meistens ☐
- Manchmal ☐
- Kaum ☐
- Nie ☐

A25. Falls nein, warum?

A26. **Die Rezepte, die ich bekommen habe, waren nützlich.**

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A27. **Falls unzutreffend, warum?**

A28. **Ich fand die empfohlenen Rezepte gut.**

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A29. **Falls unzutreffend, warum?**

A30. **Ich fand die empfohlenen Rezepte sehr gesund.**

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A31. **Falls unzutreffend, warum?**

A32. **Ich fand die Erklärungen der Empfehlungen hilfreich.**

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A33. **Falls unzutreffend, warum?**

A34. **Ich fand die Erklärungen der Empfehlungen motivierend.**

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A35. **Falls unzutreffend, warum?**

A36. **Ich finde die App unnötig kompliziert.**

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A37. **Falls ja, warum?**

A38. **Ich finde die App einfach zu benutzen.**

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A39. **Falls unzutreffend, warum?**

A40. Ich würde die App weiterhin regelmäßig benutzen.

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A41. Falls unzutreffend, warum?

A42. Ich finde die App ist widersprüchlich.

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A43. Falls unzutreffend, warum?

A44. Ich finde die App ist unübersichtlich.

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A45. Falls unzutreffend, warum?

A46. Ich glaube, dass andere sehr schnell lernen, wie man die App benutzt.

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A47. Falls unzutreffend, warum?

A48. Ich fand die App sehr mühsam.

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A49. Falls unzutreffend, warum?

A50. Ich habe mich sehr selbstsicher gefühlt bei der Benutzung der App.

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A51. Falls unzutreffend, warum?

A52. Ich musste erst einige Dinge lernen bevor ich die App richtig benutzen konnte.

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A53. Falls zutreffend, warum?

A54. **Die statistische Übersicht (Fortschritte über die Zeit der Studie) war hilfreich für mich.**

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A55. **Falls unzutreffend, warum?**

A56. **Die Übersicht der relevanten Nährstoffe auf der Startseite war verständlich.**

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A57. **Falls unzutreffend, warum?**

A58. **Ich fand die visuelle Darstellung der Startseite ansprechend.**

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A59. **Falls unzutreffend, warum?**

A60. **Ich fand die Gesamtübersicht der Nährstoffe hilfreich.**

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A61. **Falls unzutreffend, warum?**

A62. **Ich fand die Detailansicht der einzelnen Nährstoffe hilfreich.**

- Eindeutig unzutreffend ☐
- Unzutreffend ☐
- Weder zutreffend noch unzutreffend ☐
- Zutreffend ☐
- Eindeutig zutreffend ☐

A63. **Falls unzutreffend, warum?**

A64. **Funktionen der Smartphone App**

- Was hat gut funktioniert?
- Was hat nicht gut funktioniert?
- Welche Funktionen würden Sie sich zusätzlich wünschen?

A65. **Gab es Probleme bei der Blutabnahme?**

- Ja ☐
- Nein ☐

A66. **Falls ja, welche?**

A67. **Gab es Probleme bei den Körpermessungen?**

- Ja ☐
- Nein ☐

A68. **Falls ja, welche?**

A69. **Welches Smartphone habe Sie während der Studie verwendet? Bitte geben Sie Herstellernamen und Modellbezeichnung mit an.**

A70. **Welche Androidversion ist/war während der Nutzung von Nutrilize auf Ihrem Smartphone installiert?**

A71. **Gab es Probleme in Zusammenhang mit der Installation bzw. Nutzung von Nutrilize auf dem verwendeten Smartphone bzw. Androidversion?**

F

QUESTIONNAIRES OF NUTRILIZE SHORT-TERM STUDY

These is the screening and end survey of the Dutch short-term study on *Nutrilize*. The Norman, Baecke, and FFQ survey are provided in their German equivalent version in Appendix G.

Sectie A: Algemene informatie

A1. **Vul alstublieft uw archie deelnemer id in. Als u uw ID niet weet, kunt u deze controleren in de uitnodigingsmail.**

A2. **Vul alstublieft uw email adres in. Als u niet weet welk e-mailadres dit is, kunt u opzoeken naar welk adres uw uitnodigingsmail is verzonden.**

Sectie B: Gezondheidsinformatie

B1. **Ben je al meerderjarig?**

Ja ☐
Nee ☐

B2. **Heeft u voedselallergieën of voedselintoleranties?**

Ja ☐
Nee ☐

B3. **Heeft u last van ziekten die worden beïnvloed door uw dieet (bijvoorbeeld diabetes, lever, nieren, longen, hartaandoeningen, schildklieraandoeningen, bloedarmoede)**

Ja ☐
Nee ☐

B4. **Ben je momenteel zwanger? (Mannen mogen "Nee" tikken)**

Ja ☐
Nee ☐

B5. **Heb je momenteel een streng dieet (om gezondheids- of privéredenen)?**

Ja ☐
Nee ☐

B6. **Heb je een Android Phone versie 5.0 (Lollipop) of hoger?**

Ja ☐
Nee ☐

B7. **Heeft u reguliere internettoegang (mobiel netwerk of wifi) op uw Android-telefoon?**

Ja ☐
Nee ☐

Sectie C: Instemming onderzoeksdeelname

Informed consent form

Dit document geeft u informatie over de studie "Gepersonaliseerde voeding aanbevelingen". Voordat het onderzoek begint is het belangrijk dat u kennis neemt van de werkwijze die bij dit onderzoek gevolgd wordt en dat u instemt met vrijwillige deelname. Leest u dit document a.u.b. aandachtig door.

Doel en voordeel van het onderzoek

Het doel van deze studie is om gedragsverandering in het eten van gezonde voeding te testen met behulp van een voedingadvies app (Nutrilize). Dit onderzoek wordt uitgevoerd door Hanna Schäfer en Martijn Willemsen van de Human-Technology Interaction groep.

Procedure

U wordt gevraagd om drie sessies over een tijdsbestek van 14 dagen af te ronden. Het onderzoek is volledig online, u hoeft niet naar het lab te komen. De eerste sessie zal bestaan uit een online vragenlijst. U krijgt dan toegang tot de Nutrilize Android-applicatie. De tweede fase bestaat uit het gebruik van de applicatie gedurende de volgende 12 dagen. Op dag 14 wordt u gevraagd om de derde sessie te voltooien door het invullen van online vragenlijst vanaf uw eigen computer.

Risico's

Dit onderzoek brengt geen risico's met zich mee, en ook geen nadelige bijwerkingen. U bent niet verplicht te eten wat het systeem u adviseert en doet dit op eigen risico.

Duur

De studie duurt ongeveer 30 minuten voor sessie 1 en 15 minuten in de sessie 3. In de tussenliggende sessie 2 bent u vrij om de applicatie zo dikwijls en zo lang gebruiken en u wenst. Omdat de voordelen van de toepassing afhankelijk zijn van uw terugmelding van wat u eet, raden we u aan de applicatie minimaal één keer per dag te gebruiken. Deze actie duurt ongeveer 5 minuten per dag.

Participanten

U bent geselecteerd omdat u als participant geregistreerd staat in de participanten database van de Human-Technology Interaction group van de Technische Universiteit Eindhoven.

Vrijwillig

Uw deelname is geheel vrijwillig. U kunt zonder opgaaf van redenen weigeren mee te doen aan het onderzoek en uw deelname op welk moment dan ook afbreken. Ook kunt u nog achteraf (binnen 24 uur) weigeren dat uw gegevens voor het onderzoek mogen worden gebruikt. Dit alles blijft te allen tijde zonder nadelige gevolgen.

Compensatie

U krijgt 7,50 euro betaald voor het invullen van de volledige studie (sessie 1 en 3). Daarbovenop zult u een bonus van 5,00 euro ontvangen bij het invoeren van uw voedselinname voor ten minste de helft van de dagen, of 10,00 euro bij het invoeren van de gegevens op alle dagen.

Vertrouwelijkheid

Bij alle onderzoeken van Human-Technology Interaction wordt gewerkt volgens de ethische code van het NIP (Nederlands Instituut voor Psychologen). Wij delen geen persoonlijke informatie over u met mensen buiten het onderzoeksteam. Er worden geen video- of audio-opnames gemaakt die u zouden kunnen identificeren. De informatie die we met dit onderzoek verzamelen wordt gebruikt voor het schrijven van wetenschappelijke publicaties en wordt slechts op groepsniveau gerapporteerd. Alles gebeurt geheel anoniem en niets kan naar u herleid worden.

Verdere informatie

Als u meer informatie over dit onderzoek wilt kunt u vragen Hanna Schäfer (contact e-mail: h.j.schafer@tue.nl). Als u klachten heeft over deze studie, neem dan contact op met de begeleider, Martijn Willemsen (m.c.willemsen@tue.nl).

Sectie A: Algemene informatie

A1. **Vul alstublieft uw archie deelnemer id in. Als je uw ID niet weet, kunt je deze controleren in de uitnodigingsmail.**

☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

A2. **Heb je ooit in de Nutrilize app de aanbevelingen voor kookrecepten bekeken?**

Ja ☐

Nee ☐

Sectie B: Perceptie van aanbevelingen

B1. **In hoeverre je het eens of oneens met de volgende uitspraken over je perceptie van de aanbevelingen?**

	Zeer oneens	Mee oneens	Niet mee oneens/ Niet eens	Mee eens	Zeer mee eens
De aanbevolen recepten waren relevant voor mijn gezondheid.	☐	☐	☐	☐	☐
De aanbevolen recepten oogden ongezond.	☐	☐	☐	☐	☐
Het eten van de aanbevolen maaltijden zou mijn gezondheid verbeteren.	☐	☐	☐	☐	☐
De aanbevolen recepten waren gezonder dan het eten wat ik normaal eet.	☐	☐	☐	☐	☐
De aanbevolen recepten kunnen me helpen bij het bereiken van mijn gezondheidsdoelen.	☐	☐	☐	☐	☐

B2. **In hoeverre je het eens of oneens met de volgende uitspraken over je perceptie van de aanbevelingen?**

	Zeer oneens	Mee oneens	Niet mee oneens/ Niet eens	Mee eens	Zeer mee eens
De aanbevolen recepten pasten bij mijn smaakvoorkeuren.	☐	☐	☐	☐	☐
De aanbevolen recepten oogden niet erg smakelijk.	☐	☐	☐	☐	☐
De aanbevolen recepten waren lekkerder dan het eten wat ik normaal eet.	☐	☐	☐	☐	☐
De aanbevolen recepten bevatten weinig recepten die bij mijn smaak passen.	☐	☐	☐	☐	☐

B3. **In hoeverre je het eens of oneens met de volgende uitspraken over je perceptie van de aanbevelingen?**

	Zeer oneens	Mee oneens	Niet mee oneens/ Niet eens	Mee eens	Zeer mee eens
De aanbevolen recepten waren heel divers.	☐	☐	☐	☐	☐
Alle aanbevolen recepten leken op elkaar.	☐	☐	☐	☐	☐
De lijst met aanbevolen recepten bevatte veel verschillende soorten recepten .	☐	☐	☐	☐	☐
De meeste recepten waren van hetzelfde type.	☐	☐	☐	☐	☐

B4. **In hoeverre je het eens of oneens met de volgende uitspraken over je perceptie van de aanbevelingen?**

	Zeer oneens	Mee oneens	Niet mee oneens/ Niet eens	Mee eens	Zeer mee eens
De aanbevolen recepten waren goed gepersonaliseerd .	☐	☐	☐	☐	☐
De aanbevolen recepten waren goed aangepast aan mijn eetgewoontes.	☐	☐	☐	☐	☐
Andere mensen zouden waarschijnlijk andere recepten aanbevolen hebben gekregen.	☐	☐	☐	☐	☐
Mijn aanbevelingen helpen mij meer dan dat ze anderen zouden helpen.	☐	☐	☐	☐	☐

B5. **In hoeverre je het eens of oneens met de volgende uitspraken over je perceptie van de aanbevelingen?**

	Zeer oneens	Mee oneens	Niet mee oneens/ Niet eens	Mee eens	Zeer mee eens
De aanbevolen recepten waren lastig te bereiden.	☐	☐	☐	☐	☐
Het koste veel doorzettingsvermogen om de aanbevolen recepten te eten in plaats van andere opties.	☐	☐	☐	☐	☐
Het was makkelijk om me aan de aanbevolen recepten te houden.	☐	☐	☐	☐	☐
De aanbevolen recepten pasten goed bij mijn levensstijl.	☐	☐	☐	☐	☐

Sectie C: Algehele indruk van de aanbevelingen

C1. **In hoeverre bent je het eens of oneens met de volgende uitspraken over je interactie met de aanbevelingen?**

	Zeer oneens	Mee oneens	Niet mee oneens/ Niet eens	Mee eens	Zeer mee eens
Ik ben blij met de recepten die ik gekozen heb.	☐	☐	☐	☐	☐
De door mij gekozen recepten pasten niet bij mijn voorkeur.	☐	☐	☐	☐	☐
Sommige van de recepten die ik gekozen heb gaan tot mijn favorieten behoren.	☐	☐	☐	☐	☐
Ik zou sommige recepten die ik gekozen heb ook aan anderen aanbevelen.	☐	☐	☐	☐	☐
Ik was teleurgesteld in de recepten die ik heb gekozen.	☐	☐	☐	☐	☐
Het kiezen van een aanbevolen recept was overweldigend.	☐	☐	☐	☐	☐

	Zeer oneens	Mee oneens	Niet mee oneens/ Niet eens	Mee eens	Zeer mee eens
Het vergelijken van de aanbevolen recepten kostte veel moeite.	☐	☐	☐	☐	☐
Ik ben meerdere keren van gedachten veranderd voordat ik een recept koos.	☐	☐	☐	☐	☐
Het was gemakkelijk om een van de aanbevolen recepten te kiezen.	☐	☐	☐	☐	☐

Sectie D: Algehele indruk van de app

D1. In hoeverre ben je het eens of oneens met de volgende uitspraken over de Nutrilize app?

	Zeer oneens	Mee oneens	Niet mee oneens/ Niet eens	Mee eens	Zeer mee eens
De Nutrilize app werkt heel gemakkelijk.	☐	☐	☐	☐	☐
Ik moest veel moeite investeren om de Nutrilize app te leren gebruiken.	☐	☐	☐	☐	☐
Het kost erg veel klikken en handelingen om de Nutrilize App te kunnen gebruiken.	☐	☐	☐	☐	☐
Het gebruik van de Nutrilize app kost weinig tijd.	☐	☐	☐	☐	☐
Het kost te veel interactie voordat de Nutrilize App goede aanbevelingen geeft.	☐	☐	☐	☐	☐
Ik zou deze Nutrilize App aan anderen aanbevelen.	☐	☐	☐	☐	☐
De Nutrilize App maakt me bewuster van mijn mogelijkheden om mijn voeding aan te passen.	☐	☐	☐	☐	☐
Met de Nutrilize App kan ik betere dieet keuzes maken.	☐	☐	☐	☐	☐
Het gebruiken van de Nutrilize App is een plezierige ervaring.	☐	☐	☐	☐	☐

Sectie E: Een aantal vragen over jezelf als persoon

E1. In hoeverre ben je het eens of oneens met de volgende uitspraken over jezelf?

	Zeer oneens	Mee oneens	Niet mee oneens/ Niet eens	Mee eens	Zeer mee eens
Ik vind het moeilijk om slechte gewoontes te doorbreken.	☐	☐	☐	☐	☐
Ik raak gemakkelijk afgeleid.	☐	☐	☐	☐	☐
Ik zeg ongepaste dingen.	☐	☐	☐	☐	☐
Ik weiger dingen die slecht voor me zijn, zelfs als ze leuk zijn.	☐	☐	☐	☐	☐
Ik ben goed in het weerstaan van verleiding.	☐	☐	☐	☐	☐

	Zeer oneens	Mee oneens	Niet mee oneens/ Niet eens	Mee eens	Zeer mee eens
Mensen zullen zeggen dat ik een zeer sterke zelfdiscipline heb.	☐	☐	☐	☐	☐
Plezier en vermaak zorgen er soms voor dat ik niet aan het werk kan.	☐	☐	☐	☐	☐
Ik doe vaak dingen die op het moment goed voelen, maar waarvan ik later spijt krijg.	☐	☐	☐	☐	☐
Soms kan ik mezelf er niet van weerhouden iets te doen, zelfs als ik weet dat het verkeerd is.	☐	☐	☐	☐	☐
Ik handel vaak zonder alle alternatieven goed te doordenken.	☐	☐	☐	☐	☐

Sectie F: Nog een aantal vragen over jezelf als persoon

F1. In hoeverre ben je het eens of oneens met de volgende uitspraken over jezelf?

	Zeer oneens	Mee oneens	Niet mee oneens/ Niet eens	Mee eens	Zeer mee eens
Als een familielid me een plezier doet, ben ik erg geneigd om iets terug te doen.	☐	☐	☐	☐	☐
Ik betaal een gunst altijd terug.	☐	☐	☐	☐	☐
Ik ben van mening dat zeldzame/schaarse producten waardevoller zijn dan massaproducten.	☐	☐	☐	☐	☐
Wanneer mijn favoriete winkel voorgoed gaat sluiten, zou ik hem bezoeken omdat dat mijn laatste kans is.	☐	☐	☐	☐	☐
Ik volg altijd het advies van mijn huisarts.	☐	☐	☐	☐	☐
Wanneer een professor (leraar?) me iets vertelt, ben ik geneigd te geloven dat het waar is.	☐	☐	☐	☐	☐
Wanneer ik een afspraak maak, doe ik wat ik heb gezegd.	☐	☐	☐	☐	☐
Ik probeer alles te doen wat ik ook beloofd heb te doen.	☐	☐	☐	☐	☐
Als iemand uit mijn sociale netwerk me over een goed boek informeert, neig ik ernaar het te lezen.	☐	☐	☐	☐	☐
Als ik in een nieuwe situatie ben, kijk ik naar anderen om te zien wat ik moet doen.	☐	☐	☐	☐	☐
Ik accepteer advies vanuit mijn sociale netwerk.	☐	☐	☐	☐	☐
Als ik iemand leuk vind, ben ik meer geneigd hem of haar te geloven.	☐	☐	☐	☐	☐

Sectie G: Jouw mening over technologie

G1. In hoeverre ben je het eens of oneens met de volgende uitspraken over technologie?

	Zeer oneens	Mee oneens	Niet mee oneens/ Niet eens	Mee eens	Zeer mee eens
Ik voel me volledig op mijn gemak bij het werken met Android-applicaties.	☐	☐	☐	☐	☐
Ik ben heel tevreden over hoe het gaat als ik Android-applicaties gebruik.	☐	☐	☐	☐	☐
Ik heb er altijd vertrouwen in dat de juiste dingen gebeuren als ik Android-applicaties gebruik.	☐	☐	☐	☐	☐
Het lijkt erop dat er zaken in orde komen als ik Android-applicaties gebruik.	☐	☐	☐	☐	☐
Ik geloof dat de meeste technologieën effectief zijn in het bereiken waarvoor ze zijn ontworpen.	☐	☐	☐	☐	☐
Het merendeel van technologieën is uitstekend.	☐	☐	☐	☐	☐
De meeste technologieën hebben de functies die nodig zijn in hun domein.	☐	☐	☐	☐	☐
Ik denk dat de meeste technologieën me in staat stellen om te doen wat ik moet doen.	☐	☐	☐	☐	☐
Mijn gebruikelijke benadering is om nieuwe technologieën te vertrouwen totdat ze bewijzen dat ik ze niet moet vertrouwen.	☐	☐	☐	☐	☐
Ik vertrouw meestal een technologie totdat deze me een reden geeft om het niet te vertrouwen.	☐	☐	☐	☐	☐
Over het algemeen geef ik een technologie het voordeel van de twijfel wanneer ik deze voor het eerst gebruik.	☐	☐	☐	☐	☐

Sectie H: Kookgewoonten

H1. Wat voor soort gerechten kook je op dit moment voornamelijk?

- Ik bereid vooral gerechten op basis van verse/niet bereide ingrediënten ('zonder pakjes en zakjes') ☐
- Ik maak gebruik van kant-en-klare ingrediënten om een complete maaltijd te maken (gebruik bijvoorbeeld kant-en-klare sauzen) ☐
- Kook gemaksvoedsel of kant-en-klaar maaltijden ☐
- Kook helemaal niet ☐

H2. Hoe vaak bereid je in een normale week een hoofdmaaltijd voor op basis van verse/niet bereide ingrediënten?

- Dagelijks ☐
- 4-6 keer per week ☐
- 2-3 keer per week ☐
- Een keer per week ☐
- Minder dan één keer per week ☐
- Nooit ☐

H3. Hoe zeker ben je over de volgende zaken?

	Zeer onzeker	Onzeker	Zeker	Zeer zeker
… koken met verse/niet bereide ingrediënten?	☐	☐	☐	☐
… het volgen van een eenvoudig recept?	☐	☐	☐	☐
… voedsel te proeven dat je nog niet eerder hebt gegeten?	☐	☐	☐	☐
… het bereiden en koken van nieuwe voedingsmiddelen en recepten?	☐	☐	☐	☐

Bedankt voor uw deelname aan onze studie. Om uw compensatie te betalen, hebben we uw bankgegevens nodig. Je kunt deze hier invoeren:

https://www.nutrilize.de/limesurvey/index.php/744515?lang=nl

of per e-mail verzenden naar hanna.schaefer@tum.de. Als we geen IBAN-informatie van je ontvangen, ontvangt je een voucher van bol.com.

G

QUESTIONNAIRES OF NUTRILIZE LONG-TERM STUDY

Teil A:

A1. **Stimmen Sie zu, dass Ihre Daten aus dem Screening Fragebogen für Studienzwecke genutzt werden dürfen?**

- Ja ☐
- Nein ☐

Teil B:

B1. **Alter:**

- Jünger als 18 Jahre ☐
- 18 ☐
- 19 ☐
- 20 ☐
- 21 ☐
- 22 ☐
- 23 ☐
- 24 ☐
- 25 ☐
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74 ☐
75 ☐
76 ☐
77 ☐
78 ☐
79 ☐
80 ☐
Älter als 80 Jahre ☐

B2. Geschlecht:

weiblich ☐
männlich ☐

B3. Körpermaße:

Bitte geben Sie Gewicht in kg und Größe, Hüft- und Taillenumfang in cm an.

Gewicht
Größe
Hüftumfang
Taillenumfang

Teil C:

Ihr BMI ist: {round(BMIeq,2)}

C1. {KOPM0_SQ002/100}

C2. {KOPM0_SQ001/(Grose*Grose)}

Teil D:

D1. Sind Sie schwanger, stillen Sie oder planen Sie in den kommenden Monaten schwanger zu werden?

Ja ☐
Nein ☐

D2. Haben Sie von Ihrem Arzt die Anordnung erhalten, aus gesundheitlichen Gründen (z.B. Diabetes, Zöliakie, chronische Erkrankungen), Diät zu halten?

Ja ☐
Nein ☐

D3. Erhalten Sie von einem Ernährungsberater derzeit einen Diätplan?

Ja ☐
Nein ☐

D4. Leiden Sie an einer Nahrungsintoleranz oder einer Nahrungsmittelallergie?

Ja ☐
Nein ☐

D5. Wenn ja, welche?

D6. Leiden Sie an einer der folgenden Erkrankungen?

	Ja	Nein
Bluterkrankheit	☐	☐
Alkoholabhängigkeit	☐	☐
Drogenabhängigkeit	☐	☐
Depression	☐	☐
Erkrankungen, welche die Nährstoffresorption, Verdauungsfunktion, Verstoffwechselung oder Ausscheidung betreffen	☐	☐

D7. Haben Sie eine Internet flatrate?

Ja ☐
Nein ☐

D8. **Besitzen Sie ein Android Smartphone mit Version >5.0 (Lollipop)?**

Ja ☐

Nein (iPhone, Windows Phone, Ältere Android Handys ☐

D9. **Haben Sie Zugang zu einer Körperwaage?**

Ja ☐

Nein ☐

D10. **Nehmen Sie regelmäßig Medikamente ein (Ausnahme: orale Kontrazeptiva)?**

Ja ☐

Nein ☐

D11. **Wenn ja, welche und warum?**

Teil E:

Leiden Sie an einer der folgenden Erkrankungen oder wurde einer der folgenden Erkrankungen bei Ihnen schon einmal diagnostiziert?

E1. **Krebs (innerhalb der letzten 3 Jahre)**

Ja ☐

Nein ☐

E2. **Wenn ja, sind Sie in ärztlicher Behandlung?**

Ja ☐

Nein ☐

E3. **Um welche Krebsform handelt es sich?**

E4. **Hypertonie (hoher Blutdruck)**

Ja ☐

Nein ☐

E5. **Wenn ja, sind Sie in ärztlicher Behandlung?**

Ja ☐

Nein ☐

E6. **Allergien**

Ja ☐

Nein ☐

E7. **Wenn ja, sind Sie in ärztlicher Behandlung?**

Ja ☐

Nein ☐

E8. **Um welche Allergien handelt es sich dabei?**

E9. **Chronische Erkrankungen (z.B. Diabetes, Leber-, Nieren-, Lungen-, Herzerkrankungen, Schilddrüsenerkrankungen, Anämie)**

Ja ☐

Nein ☐

E10. **Wenn ja, sind Sie in ärztlicher Behandlung?**

Ja ☐

Nein ☐

E11. **Um welche Erkrankung(en) handelt es sich?**

Teil F:

F1. **Leiden Sie an einer Erkrankung, die in der vorherigen Auflistung nicht genannt wurde?**

Ja ☐

Nein ☐

F2. **Wenn ja, welche?**

F3. **Haben Sie andere Beschwerden, die Ihre körperliche Aktivität beeinflussen?**

Ja ☐

Nein ☐

F4. **Wenn ja, welche?**

Teil A:

A1. **Bitte geben Sie hier Ihren persönlichen Tokencode ein, der beim 1. Screening für Sie generiert wurde:**

Teil B: Brot

B1. **Wie oft haben Sie die folgenden Lebensmittelgruppen in den letzten 6 Monaten gegessen?**

	Nie/Seltener als 1x pro Monat	1-3x pro Monat	1x pro Woche	2-4x pro Woche	5-6x pro Woche	1x pro Tag	2-3x pro Tag	4-5x pro Tag	Mehr als 6x pro Tag
Weißbrot									
Graubrot, Schwarzbrot, Mischbrot, Mehrkornbrot									
Vollkornbrot									
Brötchen, Semmel, Wecke									
Roggenbrötchen, -semmel, -wecke									
Mehrkornbrötchen, -semmel, -wecke									
Zwieback									
Knäckebrot									

B2. **Wählen Sie die von Ihnen üblich verzehrte Portionsgröße dieser Lebensmittelgruppe aus.**

	Sehr Klein	Klein (wie auf Abbildung 1)	Klein/Medium	Medium (wie auf Abbildung 2)	Medium/Groß	Groß (wie auf Abbildung 3)	Sehr groß	Eigene Angaben (Gramm)
Weißbrot								
Graubrot, Schwarzbrot, Mischbrot, Mehrkornbrot								
Vollkornbrot								
Brötchen, Semmel, Wecke								
Roggenbrötchen, -semmel, -wecke								
Mehrkornbrötchen, -semmel, -wecke								
Zwieback								
Knäckebrot								

B3. **Eigene Angaben**
Gramm:

Weißbrot	
Graubrot, Schwarzbrot, Mischbrot, Mehrkornbrot	
Vollkornbrot	
Brötchen, Semmel, Wecke	
Roggenbrötchen, -semmel, -wecke	
Mehrkornbrötchen, -semmel, -wecke	
Zwieback	
Knäckebrot	

Teil C: Cerealien

C1. **Wie oft haben Sie die folgenden Lebensmittelgruppen in den letzten 6 Monaten gegessen?**

	Nie/Seltener als 1x pro Monat	1-3x pro Monat	1x pro Woche	2-4x pro Woche	5-6x pro Woche	1x pro Tag	2-3x pro Tag	4-5x pro Tag	Mehr als 6x pro Tag
Haferbrei									
Vollkorngetreideflocken									
Nicht-Vollkorngetreideflocken z.B. Cornflakes									
Müsli									

C2. **Wählen Sie die von Ihnen üblich verzehrte Portionsgröße dieser Lebensmittelgruppe aus.**

	Sehr klein	Klein (wie auf Abbildung 1)	Klein/Medium	Medium (wie auf Abbildung 2)	Medium/Groß	Groß (wie auf Abbildung 3)	Sehr groß	Eigene Angaben (Gramm)
Haferbrei								
Vollkorngetreideflocken								
Nicht-Vollkorngetreideflocken z.B. Cornflakes								
Müsli								

C3. **Eigene Angaben**
Gramm:

Haferbrei	

Vollkorngetreideflocken	
Nicht-Vollkorngetreideflocken z.B. Cornflakes	
Müsli	

Teil D: Kartoffeln, Reis, Pasta

D1. Wie oft haben Sie die folgenden Lebensmittelgruppen in den letzten 6 Monaten gegessen?

	Nie/Seltener als 1x pro Monat	1-3x pro Monat	1x pro Woche	2-4x pro Woche	5-6x pro Woche	1x pro Tag	2-3x pro Tag	4-5x pro Tag	Mehr als 6x pro Tag
Kartoffelpüree, gebackene Kartoffeln, Bratkartoffeln									
Kartoffeln gekocht, Pellkartoffeln									
Kartoffeln zubereitet (z.B. Kartoffelsalat, Kartoffelgratin)									
Pommes frites									
Reis									
Vollkornreis, Buchweizen, Graupen									
Nudeln, Pasta, Couscous, Polenta									
Vollkornnudeln, Vollkornpasta									
Lasagne, Mousaka, Ravioli, Tortellini									
Pizza, Calzone									
Klöße, Knödel									

D2. Wählen Sie die von Ihnen üblich verzehrte Portionsgröße dieser Lebensmittelgruppe aus.

	Sehr klein	Klein (wie auf Abbildung 1)	Klein/Medium	Medium (wie auf Abbildung 2)	Medium/Groß	Groß (wie auf Abbildung 3)	Sehr groß	Eigene Angaben (Gramm)
Kartoffelpüree, gebackene Kartoffeln, Bratkartoffeln								
Kartoffeln gekocht, Pellkartoffeln								
Kartoffeln zubereitet (z.B. Kartoffelsalat, Kartoffelgratin)								
Pommes frites								
Reis								
Vollkornreis, Buchweizen, Graupen								
Nudeln, Pasta, Couscous, Polenta								
Vollkornnudeln, Vollkornpasta								
Lasagne, Mousaka, Ravioli, Tortellini								
Pizza, Calzone								
Klöße, Knödel								

D3. Eigene Angaben

Gramm:

Kartoffelpüree, gebackene Kartoffeln, Bratkartoffeln	
Kartoffeln gekocht, Pellkartoffeln	
Kartoffeln zubereitet (z.B. Kartoffelsalat, Kartoffelgratin)	
Pommes frites	
Reis	
Vollkornreis, Buchweizen, Graupen	
Nudeln, Pasta, Couscous, Polenta	
Vollkornnudeln, Vollkornpasta	
Lasagne, Mousaka, Ravioli, Tortellini	
Pizza, Calzone	
Klöße, Knödel	

Teil E: Fleisch und Fisch

E1. Wie oft haben Sie die folgenden Lebensmittelgruppen in den letzten 6 Monaten gegessen?

	Nie/Seltener als 1x pro Monat	1-3x pro Monat	1x pro Woche	2-4x pro Woche	5-6x pro Woche	1x pro Tag	2-3x pro Tag	4-5x pro Tag	Mehr als 6x pro Tag
Rind, Wild (z.B. Braten, Steak, Hackfleisch)									
Schwein (z.B. Braten, Kotelett, Hackfleisch)									

	Nie/Seltener als 1x pro Monat	1-3x pro Monat	1x pro Woche	2-4x pro Woche	5-6x pro Woche	1x pro Tag	2-3x pro Tag	4-5x pro Tag	Mehr als 6x pro Tag
Lamm, Ziege (z.B. Braten, Kotelett)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Schmorgericht	☐	☐	☐	☐	☐	☐	☐	☐	☐
Hackfleischbällchen (z.B. Frikadelle, Boulette, Fleischplanzl)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Hühnchen oder anderes Geflügel z. B. Truthahn	☐	☐	☐	☐	☐	☐	☐	☐	☐
Schinkenspeck	☐	☐	☐	☐	☐	☐	☐	☐	☐
Aufschnitt (z.B. kalter Braten, Kochschinken, Corned Beef)	☐	☐	☐	☐	☐	☐	☐	☐	☐
geräucherte Wurst- und Fleischwaren (z.B. Salami, Schinken)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Brühwurst (z.B. Jagdwurst, Bockwurst, Wiener Würstchen)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Fleischpastete, Rostbratwurst	☐	☐	☐	☐	☐	☐	☐	☐	☐
Innereien (z.B. Leber, Niere)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Leberpastete	☐	☐	☐	☐	☐	☐	☐	☐	☐
panierter Fisch (z.B. Fischstäbchen, Fischfrikadelle)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Fischgerichte (z.B. Fischauflauf, Fischsuppe)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Weißer Fisch (z.B. Schellfisch, Dorsch, Kabeljau, Seezunge, Forelle)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Frischer Fettfisch, nicht geräuchert (z.B. Makrele, Thunfisch, Sardine, Hering, Lachs)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Fischkonserve (z.B. Makrele, Thunfisch, Sardine, Lachs)	☐	☐	☐	☐	☐	☐	☐	☐	☐
geräucherter Fisch (z.B. Lachs, Makrele)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Schalentiere, Krabben, Garnelen	☐	☐	☐	☐	☐	☐	☐	☐	☐
Kaviar	☐	☐	☐	☐	☐	☐	☐	☐	☐
Sushi	☐	☐	☐	☐	☐	☐	☐	☐	☐

E2. Wählen Sie die von Ihnen üblich verzehrte Portionsgröße dieser Lebensmittelgruppe aus.

	Sehr klein	Klein (wie auf Abbildung 1)	Klein/Medium	Medium (wie auf Abbildung 2)	Medium/Groß	Groß (wie auf Abbildung 3)	Sehr groß	Eigene Angaben (Gramm)
Rind, Wild (z.B. Braten, Steak, Hackfleisch)	☐	☐	☐	☐	☐	☐	☐	☐
Schwein (z.B. Braten, Kotelett, Hackfleisch)	☐	☐	☐	☐	☐	☐	☐	☐
Lamm, Ziege (z.B. Braten, Kotelett)	☐	☐	☐	☐	☐	☐	☐	☐
Schmorgericht	☐	☐	☐	☐	☐	☐	☐	☐
Hackfleischbällchen (z.B. Frikadelle, Boulette, Fleischplanzl)	☐	☐	☐	☐	☐	☐	☐	☐
Hühnchen oder anderes Geflügel z. B. Truthahn	☐	☐	☐	☐	☐	☐	☐	☐
Schinkenspeck	☐	☐	☐	☐	☐	☐	☐	☐
Aufschnitt (z.B. kalter Braten, Kochschinken, Corned Beef)	☐	☐	☐	☐	☐	☐	☐	☐
Geräucherte Wurst- und Fleischwaren (z.B. Salami, Schinken)	☐	☐	☐	☐	☐	☐	☐	☐
Brühwurst (z.B. Jagdwurst, Bockwurst, Wiener Würstchen)	☐	☐	☐	☐	☐	☐	☐	☐
Fleischpastete, Rostbratwurst	☐	☐	☐	☐	☐	☐	☐	☐
Innereien (z.B. Leber, Niere)	☐	☐	☐	☐	☐	☐	☐	☐
Leberpastete	☐	☐	☐	☐	☐	☐	☐	☐
panierter Fisch (z.B. Fischstäbchen, Fischfrikadelle)	☐	☐	☐	☐	☐	☐	☐	☐
Fischgerichte (z.B. Fischauflauf, Fischsuppe)	☐	☐	☐	☐	☐	☐	☐	☐
Weißer Fisch (z.B. Schellfisch, Dorsch, Kabeljau, Seezunge, Forelle)	☐	☐	☐	☐	☐	☐	☐	☐
Frischer Fettfisch, nicht geräuchert (z.B. Makrele, Thunfisch, Sardine, Hering, Lachs)	☐	☐	☐	☐	☐	☐	☐	☐
Fischkonserve (z.B. Makrele, Thunfisch, Sardine, Lachs)	☐	☐	☐	☐	☐	☐	☐	☐
geräucherter Fisch (z.B. Lachs, Makrele)	☐	☐	☐	☐	☐	☐	☐	☐
Schalentiere, Krabben, Garnelen	☐	☐	☐	☐	☐	☐	☐	☐
Kaviar	☐	☐	☐	☐	☐	☐	☐	☐
Sushi	☐	☐	☐	☐	☐	☐	☐	☐

E3. **Eigene Angaben**
Gramm:

Rind, Wild (z.B. Braten, Steak, Hackfleisch)	
Schwein (z.B. Braten, Kotelett, Hackfleisch)	
Lamm, Ziege (z.B. Braten, Kotelett)	
Schmorgericht	
Hackfleischbällchen (z.B. Frikadelle, Boulette, Fleischplanzl)	
Hühnchen oder anderes Geflügel z. B. Truthahn	
Schinkenspeck	
Aufschnitt (z.B. kalter Braten, Kochschinken, Corned Beef)	
geräucherte Wurst- und Fleischwaren (z.B. Salami, Schinken)	
Brühwurst (z.B. Jagdwurst, Bockwurst, Wiener Würstchen)	
Fleischpastete, Rostbratwurst	
Innereien (z.B. Leber, Niere)	
Leberpastete	
panierter Fisch (z.B. Fischstäbchen, Fischfrikadelle)	
Fischgerichte (z.B. Fischauflauf, Fischsuppe)	
Weißer Fisch (z.B. Schellfisch, Dorsch, Kabeljau, Seezunge, Forelle)	
Frischer Fettfisch, nicht geräuchert (z.B. Makrele, Thunfisch, Sardine, Hering, Lachs)	
Fischkonserve (z.B. Makrele, Thunfisch, Sardine, Lachs)	
geräucherter Fisch (z.B. Lachs, Makrele)	
Schalentiere, Krabben, Garnelen	
Kaviar	
Sushi	

Teil F: Milch und Milchprodukte

F1. **Wie oft haben Sie die folgenden Lebensmittelgruppen in den letzten 6 Monaten gegessen?**

	Nie/Seltener als 1x pro Monat	1-3x pro Monat	1x pro Woche	2-4x pro Woche	5-6x pro Woche	1x pro Tag	2-3x pro Tag	4-5x pro Tag	Mehr als 6x pro Tag
Vollmilch (≥ 3,5% Fett)	☐	☐	☐	☐	☐	☐	☐	☐	☐
fettarme Milch (1,5-1,8% Fett)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Magermilch, entrahmte Milch (0,3-0,5% Fett)	☐	☐	☐	☐	☐	☐	☐	☐	☐
saure Sahne, Schmand	☐	☐	☐	☐	☐	☐	☐	☐	☐
Schlagsahne	☐	☐	☐	☐	☐	☐	☐	☐	☐
Joghurt (<3% Fett)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Joghurt (≥3% Fett)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Früchtejoghurt (<3% Fett)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Früchtejoghurt (≥3% Fett)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Quark	☐	☐	☐	☐	☐	☐	☐	☐	☐
Sahnejoghurt (10% Fett)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Milchshake	☐	☐	☐	☐	☐	☐	☐	☐	☐
Käse > 60% Fett i. Tr. (z.B. Brie, Frischkäse, Butterkäse)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Käse 46 - 60% Fett i. Tr. (z.B. Gouda, Tilsiter, Edamer, Mozzarella, Feta, Gorgonzola, Maasdamer)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Käse 31 - 45% Fett i. Tr. (z.B. Limburger, Schmelzkäse, Parmesan)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Käse 10 - 30% Fett i. Tr. (z.B. Harzer Käse, Hüttenkäse)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Ei (gekocht, Rührei, Spiegelei, Omelett)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Quiche	☐	☐	☐	☐	☐	☐	☐	☐	☐
Salatdressing, Mayonnaise (niedriger Fettgehalt)	☐	☐	☐	☐	☐	☐	☐	☐	☐

	Nie/Seltener als 1x pro Monat	1-3x pro Monat	1x pro Woche	2-4x pro Woche	5-6x pro Woche	1x pro Tag	2-3x pro Tag	4-5x pro Tag	Mehr als 6x pro Tag
Salatdressing, Mayonnaise (hoher Fettgehalt)									
andere Salatdressings z.B. Vinaigrette									

F2. Wählen Sie die von Ihnen üblich verzehrte Portionsgröße dieser Lebensmittelgruppe aus.

	Sehr klein	Klein (wie auf Abbildung 1)	Klein/Medium	Medium (wie auf Abbildung 2)	Medium/Groß	Groß (wie auf Abbildung 3)	Sehr groß	Eigene Angaben (Gramm)
Vollmilch (≥ 3,5% Fett)								
fettarme Milch (1,5-1,8% Fett)								
Magermilch, entrahmte Milch (0,3-0,5% Fett)								
saure Sahne, Schmand								
Schlagsahne								
Joghurt (<3% Fett)								
Joghurt (≥3% Fett)								
Früchtejoghurt (<3% Fett)								
Früchtejoghurt (≥3% Fett)								
Quark								
Sahnejoghurt (10% Fett)								
Milchshake								
Käse > 60% Fett i. Tr. (z.B. Brie, Frischkäse, Butterkäse)								
Käse 46 - 60% Fett i. Tr. (z.B. Gouda, Tilsiter, Edamer, Mozzarella, Feta, Gorgonzola, Maasdamer)Feta								
Käse 31 - 45% Fett i. Tr. (z.B. Limburger, Schmelzkäse, Parmesan)								
Käse 10 - 30% Fett i. Tr. (z.B. Harzer Käse, Hüttenkäse)								
Ei (gekocht, Rührei, Spiegelei, Omelett)Rührei								
Quiche								
Salatdressing, Mayonnaise (niedriger Fettgehalt)								
Salatdressing, Mayonnaise (hoher Fettgehalt)								

	Sehr klein	Klein (wie auf Abbildung 1)	Klein/Medium	Medium (wie auf Abbildung 2)	Medium/Groß	Groß (wie auf Abbildung 3)	Sehr groß	Eigene Angaben (Gramm)
andere Salatdressings z.B. Vinaigrette								

F3. Eigene Angaben

Gramm/Milliliter:

Vollmilch (≥ 3,5% Fett)	
fettarme Milch (1,5-1,8% Fett)	
Magermilch, entrahmte Milch (0,3-0,5% Fett)	
saure Sahne, Schmand	
Schlagsahne	
Joghurt (<3% Fett)	
Joghurt (≥3% Fett)	
Früchtejoghurt (<3% Fett)	
Früchtejoghurt (≥3% Fett)	
Quark	
Sahnejoghurt (10% Fett)	
Milchshake	
Käse > 60% Fett i. Tr. (z.B. Brie, Frischkäse, Butterkäse)	
Käse 46 - 60% Fett i. Tr. (z.B. Gouda, Tilsiter, Edamer, Mozzarella, Feta, Gorgonzola, Maasdamer)	
Käse 31 - 45% Fett i. Tr. (z.B. Limburger, Schmelzkäse, Parmesan)	
Käse 10 - 30% Fett i. Tr. (z.B. Harzer Käse, Hüttenkäse)	
Ei (gekocht, Rührei, Spiegelei, Omelett)	
Quiche	
Salatdressing, Mayonnaise (niedriger Fettgehalt)	
Salatdressing, Mayonnaise (hoher Fettgehalt)	
andere Salatdressings z.B. Vinaigrette	

Teil G: Fette und Öle

G1. Wie oft haben Sie die folgenden Lebensmittelgruppen in den letzten 6 Monaten gegessen?

	Nie/Seltener als 1x pro Monat	1-3x pro Monat	1x pro Woche	2-4x pro Woche	5-6x pro Woche	1x pro Tag	2-3x pro Tag	4-5x pro Tag	Mehr als 6x pro Tag
Butter	☐	☐	☐	☐	☐	☐	☐	☐	☐
Pflanzenmargarine	☐	☐	☐	☐	☐	☐	☐	☐	☐
Margarine auf Olivenölbasis	☐	☐	☐	☐	☐	☐	☐	☐	☐
Halbfettmargarine	☐	☐	☐	☐	☐	☐	☐	☐	☐
Olivenöl	☐	☐	☐	☐	☐	☐	☐	☐	☐
andere Pflanzenöle	☐	☐	☐	☐	☐	☐	☐	☐	☐

G2. Wählen Sie die von Ihnen üblich verzehrte Portionsgröße dieser Lebensmittelgruppe aus.

	Sehr klein	Klein (wie auf Abbildung 1)	Klein/Medium	Medium (wie auf Abbildung 2)	Medium/Groß	Groß (wie auf Abbildung 3)	Sehr groß	Eigene Angaben (Gramm/Milliliter)
Butter	☐	☐	☐	☐	☐	☐	☐	☐
Pflanzenmargarine	☐	☐	☐	☐	☐	☐	☐	☐
Margarine auf Olivenölbasis	☐	☐	☐	☐	☐	☐	☐	☐
Halbfettmargarine	☐	☐	☐	☐	☐	☐	☐	☐
Olivenöl	☐	☐	☐	☐	☐	☐	☐	☐
andere Pflanzenöle	☐	☐	☐	☐	☐	☐	☐	☐

G3. Eigene Angaben
Gramm/Milliliter:

Butter	
Pflanzenmargarine	
Margarine auf Olivenölbasis	
Halbfettmargarine	
Olivenöl	
andere Pflanzenöle	

Teil H: Süßigkeiten und Snacks

H1. Wie oft haben Sie die folgenden Lebensmittelgruppen in den letzten 6 Monaten gegessen?

	Nie/Seltener als 1x pro Monat	1-3x pro Monat	1x pro Woche	2-4x pro Woche	5-6x pro Woche	1x pro Tag	2-3x pro Tag	4-5x pro Tag	Mehr als 6x pro Tag
Kekse, Plätzchen	☐	☐	☐	☐	☐	☐	☐	☐	☐
Kuchen (z.B. Rühr-, Sand-, Napf-, Obst-, Streusel-)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Torten (z.B. Sahne-, Schokolade-, Creme-, Käsekuchen)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Getreide-, Müsliriegel	☐	☐	☐	☐	☐	☐	☐	☐	☐
Croissant, Muffin, Donut	☐	☐	☐	☐	☐	☐	☐	☐	☐
Waffeln, Pfannkuchen, Crêpes	☐	☐	☐	☐	☐	☐	☐	☐	☐
Pudding, Milchreis	☐	☐	☐	☐	☐	☐	☐	☐	☐
Eiscreme	☐	☐	☐	☐	☐	☐	☐	☐	☐
Sorbet, Götterspeise	☐	☐	☐	☐	☐	☐	☐	☐	☐
Schokolade	☐	☐	☐	☐	☐	☐	☐	☐	☐
Schokoladenriegel	☐	☐	☐	☐	☐	☐	☐	☐	☐
Bonbon (z.B. Karamell-, Frucht-)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Zucker (für Kaffee, Tee)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Kartoffelchips, Flips	☐	☐	☐	☐	☐	☐	☐	☐	☐
Nüsse und Samen (z.B. Mandeln, Erdnüsse, Kürbiskerne)	☐	☐	☐	☐	☐	☐	☐	☐	☐

H2. Wählen Sie die von Ihnen üblich verzehrte Portionsgröße dieser Lebensmittelgruppe aus.

	Sehr klein	Klein (wie auf Abbildung 1)	Klein/Medium	Medium (wie auf Abbildung 2)	Medium/Groß	Groß (wie auf Abbildung 3)	Sehr groß	Eigene Angaben (Gramm)
Kekse, Plätzchen	☐	☐	☐	☐	☐	☐	☐	☐
Kuchen (z.B. Rühr-, Sand-, Napf-, Obst-, Streusel-)	☐	☐	☐	☐	☐	☐	☐	☐
Torten (z.B. Sahne-, Schokolade-, Creme-, Käsekuchen)	☐	☐	☐	☐	☐	☐	☐	☐

	Sehr klein	Klein (wie auf Abbildung 1)	Klein/Medium	Medium (wie auf Abbildung 2)	Medium/Groß	Groß (wie auf Abbildung 3)	Sehr groß	Eigene Angaben (Gramm)
Getreide-, Müsliriegel								
Croissant, Muffin, Donut								
Waffeln, Pfannkuchen, Crêpes								
Pudding, Milchreis								
Eiscreme								
Sorbet, Götterspeise								
Schokolade								
Schokoladenriegel								
Bonbon (z.B. Karamell-, Frucht-)								
Zucker (für Kaffee, Tee)								
Kartoffelchips, Flips								
Nüsse und Samen (z.B. Mandeln, Erdnüsse, Kürbiskerne)								

H3. Eigene Angaben

Gramm:

Kekse, Plätzchen	
Kuchen (z.B. Rühr-, Sand-, Napf-, Obst-, Streusel-)	
Torten (z.B. Sahne-, Schokolade-, Creme-, Käsekuchen)	
Getreide-, Müsliriegel	
Croissant, Muffin, Donut	
Waffeln, Pfannkuchen, Crêpes	
Pudding, Milchreis	
Eiscreme	
Sorbet, Götterspeise	
Schokolade	
Schokoladenriegel	
Bonbon (z.B. Karamell-, Frucht-)	
Zucker (für Kaffee, Tee)	
Kartoffelchips, Flips	
Nüsse und Samen (z.B. Mandeln, Erdnüsse, Kürbiskerne)	

Teil I: Suppen, Soßen und Aufstriche

I1. Wie oft haben Sie die folgenden Lebensmittelgruppen in den letzten 6 Monaten gegessen?

	Nie/Seltener als 1x pro Monat	1-3x pro Monat	1x pro Woche	2-4x pro Woche	5-6x pro Woche	1x pro Tag	2-3x pro Tag	4-5x pro Tag	Mehr als 6x pro Tag
Cremesuppe (z.B. Pilz-, Spargel-, Blumenkohl-)									
Gemüsesuppe (z.B. Minestrone)									
cremige Saucen (z.B. Carbonara, Käsesauce)									
Bratensauce									
Tomatensauce									
Tomatenketchup									
Konfitüre, Marmelade, Honig									
Nuss-Nougat-Creme, Erdnussbutter									

I2. Wählen Sie die von Ihnen üblich verzehrte Portionsgröße dieser Lebensmittelgruppe aus.

	Sehr klein	Klein (wie auf Abbildung 1)	Klein/Medium	Medium (wie auf Abbildung 2)	Medium/Groß	Groß (wie auf Abbildung 3)	Sehr groß	Eigene Angaben (Gramm/Milliliter)
Cremesuppe (z.B. Pilz-, Spargel-, Blumenkohl-)								
Gemüsesuppe (z.B. Minestrone)								
cremige Saucen (z.B. Carbonara, Käsesauce)								
Bratensauce								
Tomatensauce								
Tomatenketchup								
Konfitüre, Marmelade, Honig								
Nuss-Nougat-Creme, Erdnussbutter								

I3. **Eigene Angaben**
Gramm/Milliliter:

Cremesuppe (z.B. Pilz-, Spargel-, Blumenkohl-)	
Gemüsesuppe (z.B. Minestrone)	
cremige Saucen (z.B. Carbonara, Käsesauce)	
Bratensauce	
Tomatensauce	
Tomatenketchup	
Konfitüre, Marmelade, Honig	
Nuss-Nougat-Creme, Erdnussbutter	

Teil J: Getränke

J1. **Wie oft haben Sie die folgenden Lebensmittelgruppen in den letzten 6 Monaten gegessen?**

	Nie/Seltener als 1x pro Monat	1-3x pro Monat	1x pro Woche	2-4x pro Woche	5-6x pro Woche	1x pro Tag	2-3x pro Tag	4-5x pro Tag	Mehr als 6x pro Tag
Tee (z. B. Schwarz-, Grün-, Früchte-, Kräuter-)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Latte Macchiato, Cappuccino, Milchkaffee	☐	☐	☐	☐	☐	☐	☐	☐	☐
Kaffee schwarz	☐	☐	☐	☐	☐	☐	☐	☐	☐
Heiße Schokolade mit Milch	☐	☐	☐	☐	☐	☐	☐	☐	☐
Ovomaltine, Heiße Schokolade mit Wasser	☐	☐	☐	☐	☐	☐	☐	☐	☐
Soft Drinks zuckerfrei (z.B. Orangenlimonade, Zitronenlimonade)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Soft Drinks mit Zucker (z.B. Coca Cola, Orangenlimonade, Zitronenlimonade)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Fruchtsaft (100% Fruchtgehalt)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Fruchtsirup	☐	☐	☐	☐	☐	☐	☐	☐	☐
Gemüsesaft (z.B. Tomate-, Karotte-)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Wein	☐	☐	☐	☐	☐	☐	☐	☐	☐

	Nie/Seltener als 1x pro Monat	1-3x pro Monat	1x pro Woche	2-4x pro Woche	5-6x pro Woche	1x pro Tag	2-3x pro Tag	4-5x pro Tag	Mehr als 6x pro Tag
Bier	☐	☐	☐	☐	☐	☐	☐	☐	☐
Portwein, Sherry, Wermut, Likör	☐	☐	☐	☐	☐	☐	☐	☐	☐
Spirituosen (z.B. Gin, Brandy, Whiskey, Vodka)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Alkoholmixgetränke (z.B. Alkopop, Cocktail)	☐	☐	☐	☐	☐	☐	☐	☐	☐

J2. **Wählen Sie die von Ihnen üblich verzehrte Portionsgröße dieser Lebensmittelgruppe aus.**

	Sehr klein	Klein (wie auf Abbildung 1)	Klein/Medium	Medium (wie auf Abbildung 2)	Medium/Groß	Groß (wie auf Abbildung 3)	Sehr groß	Eigene Angaben (Milliliter)
Tee (z. B. Schwarz-, Grün-, Früchte-, Kräuter-)	☐	☐	☐	☐	☐	☐	☐	☐
Latte Macchiato, Cappuccino, Milchkaffee	☐	☐	☐	☐	☐	☐	☐	☐
Kaffee schwarz	☐	☐	☐	☐	☐	☐	☐	☐
Heiße Schokolade mit Milch	☐	☐	☐	☐	☐	☐	☐	☐
Ovomaltine, Heiße Schokolade mit Wasser	☐	☐	☐	☐	☐	☐	☐	☐
Soft Drinks zuckerfrei	☐	☐	☐	☐	☐	☐	☐	☐
Soft Drinks mit Zucker (z.B. Coca Cola, Orangenlimonade, Zitronenlimonade)	☐	☐	☐	☐	☐	☐	☐	☐
Fruchtsaft (100% Fruchtgehalt)	☐	☐	☐	☐	☐	☐	☐	☐
Fruchtsirup	☐	☐	☐	☐	☐	☐	☐	☐
Gemüsesaft (z.B. Tomate-, Karotte-)	☐	☐	☐	☐	☐	☐	☐	☐
Alkoholmixgetränke (z.B. Alkopop, Cocktail)	☐	☐	☐	☐	☐	☐	☐	☐

J3. **Wählen Sie die Anzahl der getrunkenen Gläser.**

	0,5	1	1,5	2	2,5	3	4	Eigene Angaben (Milliliter)
Wein	☐	☐	☐	☐	☐	☐	☐	☐
Bier	☐	☐	☐	☐	☐	☐	☐	☐
Portwein, Sherry, Wermut, Likör	☐	☐	☐	☐	☐	☐	☐	☐
Spirituosen (z.B. Gin, Brandy, Whiskey, Vodka)	☐	☐	☐	☐	☐	☐	☐	☐

J4. Eigene Angaben

Milliliter:

Tee (z. B. Schwarz-, Grün-, Früchte-, Kräuter-)	
Latte Macchiato, Cappuccino, Milchkaffee	
Kaffee schwarz	
Heiße Schokolade mit Milch	
Ovomaltine, Heiße Schokolade mit Wasser	
Soft Drinks zuckerfrei (z.B. Orangenlimonade, Zitronenlimonade)	
Soft Drinks mit Zucker (z.B. Coca Cola, Orangenlimonade, Zitronenlimonade)	
Fruchtsaft (100% Fruchtgehalt)	
Fruchtnektar (25-50% Fruchtgehalt)	
Gemüsesaft (z.B. Tomate-, Karotte-)	
Wein	
Bier	
Portwein, Sherry, Wermut, Likör	
Spirituosen (z.B. Gin, Brandy, Whiskey, Vodka)	
Alkoholmixgetränke (z.B. Alkopop, Cocktail)	

Teil K: Obst

K1. Wie oft haben Sie die folgenden Lebensmittelgruppen in den letzten 6 Monaten gegessen?

	Nie/Seltener als 1x pro Monat	1-3x pro Monat	1x pro Woche	2-4x pro Woche	5-6x pro Woche	1x pro Tag	2-3x pro Tag	4-5x pro Tag	Mehr als 6x pro Tag
Apfel									
Birne									
Orange, Zitrone, Mandarine									
Grapefruit									
Banane									
Weintrauben									
Melone, Mango									
Pfirsich, Pflaume, Zwetschge, Aprikose, Nektarine									
Beeren (z.B. Erdbeere, Himbeere)									
Kirschen									
Kiwi									
Obstkonserve									
Trockenobst (z.B. Rosine, Backpflaume)									

K2. Wählen Sie die von Ihnen üblich verzehrte Portionsgröße dieser Lebensmittelgruppe aus.

	Sehr klein	Klein (wie auf Abbildung 1)	Klein/Medium	Medium (wie auf Abbildung 2)	Medium/Groß	Groß (wie auf Abbildung 3)	Sehr groß	Eigene Angaben (Gramm)
Apfel								
Birne								
Orange, Zitrone, Mandarine								
Grapefruit								
Banane								
Weintrauben								
Melone, Mango								
Pfirsich, Pflaume, Zwetschge, Aprikose, Nektarine								
Beeren (z.B. Erdbeere, Himbeere)								
Kirschen								
Kiwi								
Obstkonserve								
Trockenobst (z.B. Rosine, Backpflaume)								

K3. Eigene Angaben

Gramm:

Apfel	

Birne	
Orange, Zitrone, Mandarine	
Grapefruit	
Banane	
Weintrauben	
Melone, Mango	
Pfirsich, Pflaume, Zwetschge, Aprikose, Nektarine	
Beeren (z.B. Erdbeere, Himbeere)	
Kirschen	
Kiwi	
Obstkonserve	
Trockenobst (z.B. Rosine, Backpflaume)	

Teil L: Gemüse

L1. Wie oft haben Sie die folgenden Lebensmittelgruppen in den letzten 6 Monaten gegessen?

	Nie/Seltener als 1x pro Monat	1-3x pro Monat	1x pro Woche	2-4x pro Woche	5-6x pro Woche	1x pro Tag	2-3x pro Tag	4-5x pro Tag	Mehr als 6x pro Tag
Möhren (Karotten, gelbe Rüben)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Kürbis	☐	☐	☐	☐	☐	☐	☐	☐	☐
Spinat	☐	☐	☐	☐	☐	☐	☐	☐	☐
Broccoli	☐	☐	☐	☐	☐	☐	☐	☐	☐
Rosenkohl	☐	☐	☐	☐	☐	☐	☐	☐	☐
Weißkohl, Rotkohl	☐	☐	☐	☐	☐	☐	☐	☐	☐
Erbsen	☐	☐	☐	☐	☐	☐	☐	☐	☐
Grüne Bohnen, Kidneybohnen, weiße Bohnen	☐	☐	☐	☐	☐	☐	☐	☐	☐
Zucchini, Aubergine	☐	☐	☐	☐	☐	☐	☐	☐	☐

	Nie/Seltener als 1x pro Monat	1-3x pro Monat	1x pro Woche	2-4x pro Woche	5-6x pro Woche	1x pro Tag	2-3x pro Tag	4-5x pro Tag	Mehr als 6x pro Tag
Blumenkohl	☐	☐	☐	☐	☐	☐	☐	☐	☐
Pastinake, Kohlrabi	☐	☐	☐	☐	☐	☐	☐	☐	☐
Spargel	☐	☐	☐	☐	☐	☐	☐	☐	☐
Zwiebel	☐	☐	☐	☐	☐	☐	☐	☐	☐
Lauch	☐	☐	☐	☐	☐	☐	☐	☐	☐
Knoblauch	☐	☐	☐	☐	☐	☐	☐	☐	☐
Pilze	☐	☐	☐	☐	☐	☐	☐	☐	☐
Paprika	☐	☐	☐	☐	☐	☐	☐	☐	☐
Sojasprossen	☐	☐	☐	☐	☐	☐	☐	☐	☐
Rettich, Radieschen	☐	☐	☐	☐	☐	☐	☐	☐	☐
Grüner Salat, Eisbergsalat, Gurke, Sellerie, Wasserkresse	☐	☐	☐	☐	☐	☐	☐	☐	☐
Tomaten	☐	☐	☐	☐	☐	☐	☐	☐	☐
Mais	☐	☐	☐	☐	☐	☐	☐	☐	☐
Rote Beete	☐	☐	☐	☐	☐	☐	☐	☐	☐
Sauerkraut	☐	☐	☐	☐	☐	☐	☐	☐	☐
Avocado	☐	☐	☐	☐	☐	☐	☐	☐	☐
Fleischersatz (z.B. Tofu, Sojafleisch)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Oliven	☐	☐	☐	☐	☐	☐	☐	☐	☐

L2. Wählen Sie die von Ihnen üblich verzehrte Portionsgröße dieser Lebensmittelgruppe aus.

	Sehr klein	Klein (wie auf Abbildung 1)	Klein/Medium	Medium (wie auf Abbildung 2)	Medium/Groß	Groß (wie auf Abbildung 3)	Sehr groß	Eigene Angaben (Gramm)
Möhren (Karotten, gelbe Rüben)	☐	☐	☐	☐	☐	☐	☐	☐
Kürbis	☐	☐	☐	☐	☐	☐	☐	☐
Spinat	☐	☐	☐	☐	☐	☐	☐	☐
Broccoli	☐	☐	☐	☐	☐	☐	☐	☐

	Sehr klein	Klein (wie auf Abbildung 1)	Klein/Medium	Medium (wie auf Abbildung 2)	Medium/Groß	Groß (wie auf Abbildung 3)	Sehr groß	Eigene Angaben (Gramm)
Rosenkohl	☐	☐	☐	☐	☐	☐	☐	☐
Weißkohl, Rotkohl	☐	☐	☐	☐	☐	☐	☐	☐
Erbsen	☐	☐	☐	☐	☐	☐	☐	☐
Grüne Bohnen, Kidneybohnen, weiße Bohnen	☐	☐	☐	☐	☐	☐	☐	☐
Zucchini, Aubergine	☐	☐	☐	☐	☐	☐	☐	☐
Blumenkohl	☐	☐	☐	☐	☐	☐	☐	☐
Pastinake, Kohlrabi	☐	☐	☐	☐	☐	☐	☐	☐
Spargel	☐	☐	☐	☐	☐	☐	☐	☐
Zwiebel	☐	☐	☐	☐	☐	☐	☐	☐
Lauch	☐	☐	☐	☐	☐	☐	☐	☐
Knoblauch	☐	☐	☐	☐	☐	☐	☐	☐
Pilze	☐	☐	☐	☐	☐	☐	☐	☐
Paprika	☐	☐	☐	☐	☐	☐	☐	☐
Sojasprossen	☐	☐	☐	☐	☐	☐	☐	☐
Rettich, Radieschen	☐	☐	☐	☐	☐	☐	☐	☐
Grüner Salat, Eisbergsalat, Gurke, Sellerie, Wasserkresse	☐	☐	☐	☐	☐	☐	☐	☐
Tomaten	☐	☐	☐	☐	☐	☐	☐	☐
Mais	☐	☐	☐	☐	☐	☐	☐	☐
Rote Beete	☐	☐	☐	☐	☐	☐	☐	☐
Sauerkraut	☐	☐	☐	☐	☐	☐	☐	☐
Avocado	☐	☐	☐	☐	☐	☐	☐	☐
Fleischersatz (z.B. Tofu, Sojafleisch)	☐	☐	☐	☐	☐	☐	☐	☐
Oliven	☐	☐	☐	☐	☐	☐	☐	☐

L3. Eigene Angaben

Gramm:

Möhren (Karotten, gelbe Rüben)	
Kürbis	
Spinat	
Broccoli	
Rosenkohl	
Weißkohl, Rotkohl	
Erbsen	
Grüne Bohnen, Kidneybohnen, weiße Bohnen	
Zucchini, Aubergine	
Blumenkohl	
Pastinake, Kohlrabi	
Spargel	
Zwiebel	
Lauch	
Knoblauch	
Pilze	
Paprika	
Sojasprossen	
Rettich, Radieschen	
Grüner Salat, Eisbergsalat, Gurke, Sellerie, Wasserkresse	
Tomaten	
Mais	
Rote Beete	
Sauerkraut	
Avocado	

Fleischersatz (z.B. Tofu, Sojafleisch) | | | | | | | | | | |

Oliven | | | | | | | | | | |

Teil M: Supplemente/ Nahrungsergänzungsmittel

M1.

Marke angeben: z.B. Centrum, Abtei, Doppelherz

Vollständiger Produktname angeben: z.B. Centrum A-Z

Was wird supplementiert?

Name des Vitamins, Mineralstoffes, Fischöl …

Wieviel?

Wie oft?

Teil A:

A1. **Bitte geben Sie hier Ihren persönlichen Tokencode ein, der beim 1. Screening für Sie generiert wurde:**

A2. **Alter:**

Jahre

A3. **Geschlecht:**

weiblich ☐

männlich ☐

A4. **Körpermaße:**

Bitte geben Sie Gewicht in kg und Größe, Hüftumfang, Taillenumfang in cm.

Gewicht:

Größe:

Hüftumfang:

Taillenumfang:

A5. **Markieren Sie Ihre durchschnittliche körperliche Aktivität während Ihrer Arbeit/Ausübung Ihres Berufs im letzten Monat und geben Sie die Häufigkeiten an:**

Überwiegend sitzend ☐

Die Hälfte der Zeit sitzend ☐

Überwiegend stehend ☐

Überwiegend laufend, manchmal Heben und Tragen von Sachen ☐

Überwiegend laufend, häufiges Heben und Tragen von Sachen ☐

Schwere handwerkliche Arbeit ☐

A6. **Wie viele Tage pro Woche arbeiten Sie?**

Tage pro Woche

A7. **Wie viele Stunden pro Tag arbeiten Sie im Durchschnitt?**

Stunden pro Tag

A8. **Wie viel Zeit verbringen Sie durchschnittlich pro Woche mit Laufen oder Fahrrad fahren?**

Stunden pro Woche

A9. **Wie viel Zeit verbringen Sie durchschnittlich pro Woche mit Haushaltsarbeiten?**

Stunden pro Woche

A10. **Wie viel Zeit verbringen Sie durchschnittlich mit Fernsehen oder Lesen pro Woche?**

Stunden pro Woche

A11. **Wie viel Zeit verbringen Sie durchschnittlich pro Woche mit sportlichen Aktivitäten?**

Stunden pro Woche

A12. **Wie viele Stunden schlafen Sie durchschnittlich an einem Tag (24 Stunden)?**

Stunden pro Tag

Teil A: Baecke Arbeitsindex

A1. **Bitte geben Sie hier Ihren persönlichen Tokencode ein, der beim 1. Screening für Sie generiert wurde:**

A2. **Wie hoch ist die körperliche Aktivität während Ihrer Arbeit?**

- Geringe Aktivität ☐
- Moderate Aktivität ☐
- Hohe Aktivität ☐

A3. **Ich arbeite sitzend.**

- Nie ☐
- Selten ☐
- Manchmal ☐
- Häufig ☐
- Immer ☐

A4. **Ich arbeite stehend.**

- Nie ☐
- Selten ☐
- Manchmal ☐
- Häufig ☐
- Immer ☐

A5. **Ich gehe während der Arbeit.**

- Nie ☐
- Selten ☐
- Manchmal ☐
- Häufig ☐
- Immer ☐

A6. **Ich hebe während meiner Arbeitszeit schwere Gewichte.**

- Nie ☐
- Selten ☐
- Manchmal ☐
- Häufig ☐
- Immer ☐

A7. **Ich bin müde nach der Arbeit.**

- Sehr häufig ☐
- Häufig ☐
- Manchmal ☐
- Selten ☐
- Nie ☐

A8. **Ich schwitze während der Arbeit.**

- Sehr häufig ☐
- Häufig ☐
- Manchmal ☐
- Selten ☐
- Nie ☐

A9. **Im Vergleich zu Gleichaltrigen ist meine Arbeit körperlicher Art.**

- Viel anstregender ☐
- Anstrengender ☐
- Genauso anstrengend ☐
- Leichter ☐
- Viel leichter ☐

Teil B: Baecke Sportindex 1

B1. **Üben Sie irgendwelche Sportarten aus?**

- Ja ☐
- Nein ☐

B2. **Im Vergleich zu Gleichaltrigen ist meine körperliche Betätigung während der Freizeit.**

- Viel höher ☐
- Höher ☐
- Genauso hoch ☐
- Geringer ☐
- Viel geringer ☐

B3. **Ich schwitze während meiner Freizeit.**

- Sehr häufig ☐
- Häufig ☐
- Manchmal ☐
- Selten ☐
- Nie ☐

B4. **Ich bin während meiner Freizeit sportlich bzw. körperlich aktiv.**

- Nie ☐
- Selten ☐
- Manchmal ☐
- Häufig ☐
- Sehr häufig ☐

Teil C: Baecke Sportindex 2

Daten zur am häufigsten ausgeübten Sportart:

C1. **Welche Intensität besitzt die Sportart, die Sie am häufigsten ausüben?**

- Geringe Intensität ☐
- Mittlere Intensität ☐
- Hohe Intensität ☐

C2. **Wieviele Stunden Sport üben Sie in der Woche aus?**

- <1 Stunde ☐
- 1-2 Stunden ☐
- 2-3 Stunden ☐
- 3-4 Stunden ☐
- >4 Stunden ☐

C3. **Wieviele Monate im Jahr üben Sie Sport aus?**

- <1 Monat ☐
- 1-3 Monate ☐
- 4-6 Monate ☐
- 7-9 Monate ☐
- >9 Monate ☐

Teil D: Baecke Sportindex 3

Daten zur am zweithäufigsten ausgeübten Sportart:

D1. **Welche Intensität besitzt die Sportart, die sie am zweithäufigsten ausüben?**

- Geringe Intensität ☐
- Mittlere Intensität ☐
- Hohe Intensität ☐

D2. **Wie viele Stunden machen Sie während der Woche Sport?**

- < 1 Stunde ☐
- 1-2 Stunden ☐
- 2-3 Stunden ☐
- 3-4 Stunden ☐
- > 4 Stunden ☐

D3. **Wieviele Monate üben Sie im Jahr Sport aus?**

- <1 Monat ☐
- 1-3 Monate ☐
- 4-6 Monate ☐
- 7-9 Monate ☐
- >9 Monate ☐

Teil E: Baecke Freizeitindex

E1. Während meiner Freizeit schaue ich fern?

- Nie ☐
- Selten ☐
- Manchmal ☐
- Häufig ☐
- Immer ☐

E2. Während meiner Freizeit gehe ich spazieren.

- Nie ☐
- Selten ☐
- Manchmal ☐
- Häufig ☐
- Immer ☐

E3. Während meiner Freizeit fahre ich Rad.

- Nie ☐
- Selten ☐
- Manchmal ☐
- Häufig ☐
- Immer ☐

E4. Wieviele Minuten gehst und/oder fährst du mit dem Rad zur und von der Arbeit/Schule/Einkäufe?

- < 5 minutes ☐
- 5-15 minutes ☐
- 15-30 minutes ☐
- 30-45 minutes ☐
- > 45 minutes ☐

Teil A: Allgemein

A1. **Token Code:**

A2. **Waren Sie Teil der Kontrollgruppe, oder hatten Sie Zugriff zur App?**

Kontrollgruppe ☐

Interventionsgruppe (App) ☐

Teil B: Sozioökonomischer Status

B1. **Ethnische Zugehörigkeit**

Kaukasisch ☐

Asiatisch ☐

Schwarzafrikanisch ☐

Sonstiges ☐

Sonstiges

B2. **Beruf**

B3. **Berufsstand**

Vollzeit ☐

Teilzeit ☐

B4. **Höchster beruflicher Ausbildungsabschluss:**

Hochschulabschluss ☐

Fachhochschulabschluss (auch Ingenieurschulabschluss) ☐

Abschluss einer Ausbildung an einer Fach-, Meister-, Technikerschule, Berufs- oder Fachakademie ☐

Abschluss einer beruflichen Ausbildung (Lehre) oder gleichwertiger Berufsfachschulabschluss ☐

Sonstiger beruflicher Abschluss (z.B. Anlernberuf, berufliches Praktikum) ☐

Noch in beruflicher Ausbildung, Student(in) ☐

Kein beruflicher Abschluss und nicht in beruflicher Ausbildung, Schüler(in) ☐

Teil C: App

C1. **Wie haben Ihnen folgende Screens gefallen?**

	Hat mir überhaupt nicht gefallen	Hat mir eher nicht gefallen	Teils / Teils	Hat mir eher gefallen	Hat mir sehr gut gefallen	Ich kenne den Screen nicht
Home Screen	☐	☐	☐	☐	☐	☐
Nährstoffübersicht	☐	☐	☐	☐	☐	☐
Nährstoffdetails	☐	☐	☐	☐	☐	☐
Kalorienübersicht	☐	☐	☐	☐	☐	☐
Sportsuche	☐	☐	☐	☐	☐	☐
Essenssuche	☐	☐	☐	☐	☐	☐
Nährstoffvorschau (Informationen zur Beeinflussung des Nährstoffhaushalts)	☐	☐	☐	☐	☐	☐
Nährstoffvorschau samt Nährstoffdetails	☐	☐	☐	☐	☐	☐
Tagebuch	☐	☐	☐	☐	☐	☐
Empfehlungen	☐	☐	☐	☐	☐	☐
Statistiken	☐	☐	☐	☐	☐	☐
Profilansicht	☐	☐	☐	☐	☐	☐
Eingabe von Präferenzen	☐	☐	☐	☐	☐	☐

C2. **Wie sehr haben Ihnen die folgenden Screens geholfen Ihre Ernährung zu verbessern?**

	Hat mir überhaupt nicht geholfen	Hat mir eher nicht geholfen	Teils / Teils	Hat mir eher geholfen	Hat mir sehr geholfen	Ich kenne den Screen nicht
Home Screen	☐	☐	☐	☐	☐	☐
Nährstoffübersicht	☐	☐	☐	☐	☐	☐
Nährstoffdetails	☐	☐	☐	☐	☐	☐
Kalorienübersicht	☐	☐	☐	☐	☐	☐
Sportsuche	☐	☐	☐	☐	☐	☐
Essenssuche	☐	☐	☐	☐	☐	☐
Nährstoffvorschau (Informationen zur Beeinflussung des Nährstoffhaushalts)	☐	☐	☐	☐	☐	☐

	Hat mir überhaupt nicht geholfen	Hat mir eher nicht geholfen	Teils / Teils	Hat mir eher geholfen	Hat mir sehr geholfen	Ich kenne den Screen nicht
Nährstoffvorschau samt Nährstoffdetails						
Tagebuch						
Empfehlungen						
Statistiken						
Profilansicht						
Eingabe von Präferenzen						

C3. Bewertung des Systems

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Teils / Teils	Stimme eher zu	Stimme voll und ganz zu
Ich kann mir sehr gut vorstellen, das System regelmäßig zu nutzen.					
Ich empfinde das System als unnötig komplex.					
Ich empfinde das System als einfach zu nutzen.					
Ich denke, dass ich technischen Support brauchen würde, um das System zu nutzen.					
Ich finde, dass die verschiedenen Funktionen des Systems gut integriert sind.					
Ich finde, dass es im System zu viele Inkonsistenzen gibt.					
Ich kann mir vorstellen, dass die meisten Leute das System schnell zu beherrschen lernen.					
Ich empfinde die Bedienung als sehr umständlich.					
Ich habe mich bei der Nutzung des Systems sehr sicher gefühlt.					
Ich musste eine Menge Dinge lernen, bevor ich mit dem System arbeiten konnte.					

C4. Bewertung der Nützlichkeit der App

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Teils / Teils	Stimme eher zu	Stimme voll und ganz zu
Nutrilize ermöglicht es mir meine Ernährung besser zu überblicken.					
Nutrilize verbessert meine Ernährung.					
Nutrilize erleichtert es mir mich gesund zu ernähren.					
Ich sehe Nutrilize als nützliches Hilfsmittel für eine gesunde Ernährung an.					

C5. Falls Nutrilize zum Kauf für ihr Smartphone verfügbar wäre, würden Sie einen Kauf in Betracht ziehen?

- Ja ☐
- Nein ☐

C6. Was wäre Ihrer Meinung nach ein angemessener Preis?

- Weniger als €2 ☐
- Zwischen €2 - €5 ☐
- Zwischen €5 - €10 ☐
- Mehr als €10 ☐

C7. Welche Zahlungsart würden Sie bevorzugen, um das Programm zu erwerben?

- Einmalzahlung ☐
- Abonnement Modell (z.B. Monatliche Gebühren) ☐
- Sonstiges ☐

Sonstiges

Teil D: Empfehlungen

D1. Inwieweit stimmen Sie den folgenden Aussagen über Ihre Wahrnehmung der Empfehlungen zu oder nicht zu?

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Teils / Teils	Stimme eher zu	Stimme voll und ganz zu
Die empfohlenen Rezepte waren für meine Gesundheit relevant.					
Die empfohlenen Rezepte sahen ungesund aus.					
Der Verzehr der empfohlenen Mahlzeiten würde meine Gesundheit verbessern.					
Die empfohlenen Rezepte waren gesünder als die Nahrung, die ich normalerweise esse.					
Die empfohlenen Rezepte können mir helfen, meine Gesundheitsziele zu erreichen.					
Die empfohlenen Rezepte entsprachen meinen Geschmacksvorlieben.					
Die empfohlenen Rezepte sahen nicht sehr lecker aus.					
Die empfohlenen Rezepte waren leckerer als das Essen, das ich normalerweise esse.					
Die Empfehlungen enthielten wenige Rezepte die meinen Geschmack treffen.					

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Teils / Teils	Stimme eher zu	Stimme voll und ganz zu
Die empfohlenen Rezepte waren sehr vielfältig.					
Alle empfohlenen Rezepte sahen gleich aus.					
Die Liste der empfohlenen Rezepte enthielt viele verschiedene Arten von Rezepten.					
Die meisten Rezepte waren vom selben Typ.					
Die empfohlenen Rezepte waren gut personalisiert.					
Die empfohlenen Rezepte waren gut an meine Essgewohnheiten angepasst.					
Anderen Leuten wären wahrscheinlich andere Rezepte empfohlen worden.					
Meine Empfehlungen helfen mir mehr als sie anderen helfen würden.					
Die empfohlenen Rezepte waren schwierig zuzubereiten.					
Es brauchte viel Durchhaltevermögen, um die empfohlenen Rezepte anstelle anderer Optionen zu essen.					
Es war einfach, sich an die empfohlenen Rezepte zu halten.					
Die empfohlenen Rezepte passen gut zu meinem Lebensstil.					

D2. Inwieweit stimmen Sie folgenden Aussagen über Ihre Interaktion mit den Empfehlungen zu oder nicht zu?

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Teils / Teils	Stimme eher zu	Stimme voll und ganz zu
Ich bin glücklich mit den von mir gewählten Rezepten.					
Die Rezepte, die ich wählte, passten nicht zu meinen Vorlieben.					
Einige der Rezepte, die ich gewählt habe, sine meine Lieblingsessen.					
Ich würde einige Rezepte, die ich gekocht habe, auch an andere weiterempfehlen.					
Ich war enttäuscht von den Rezepten, die ich gewählt habe.					
Das Auswählen aus den empfohlenen Rezepten war überwältigend.					
Der Vergleich der empfohlenen Rezepte erforderte viel Aufwand.					
Ich habe meine Meinung mehrmals geändert, bevor ich ein Rezept ausgewählt habe.					
Es war einfach, eines der empfohlenen Rezepte zu wählen.					

D3. Inwieweit stimmen Sie den folgenden Aussagen zur Nutrilize-App zu oder nicht?

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Teils / Teils	Stimme eher zu	Stimme voll und ganz zu
Die Nutrilize App funktioniert sehr einfach.					
Ich musste viel investieren, um zu lernen, wie man die Nutrilize App benutzt.					
Es braucht eine Menge Klicks und Aktionen, um die Nutrilize App zu verwenden.					
Die Verwendung der Nutrilize-App benötigt wenig Zeit.					
Es müssen zu viele Eingaben gemacht werden, bevor die Nutrilize App gute Empfehlungen gibt.					
Ich würde die Nutrilize App anderen empfehlen.					
Die Nutrilize-App macht mir meine Möglichkeiten, meine Ernährung anzupassen, bewusster.					
Mit der Nutrilize App kann ich bessere Diät-Entscheidungen treffen.					
Die Verwendung der Nutrilize App ist eine angenehme Erfahrung.					

Teil E: Visualisierung

E1. Inwieweit treffen die folgenden Aussagen zum Home Screen mit 6 Nährstoffen zu?

	Trifft überhaupt nicht zu	Trifft eher nicht zu	Teils / Teils	Trifft eher zu	Trifft voll und ganz zu
Ich finde den Home Screen verständlich.					
Ich finde den Home Screen informativ.					
Ich finde den Home Screen ansprechend.					
Ich finde den Home Screen überflüssig.					
Der Home Screen hilft mir meinen persönlichen Nährstoffstatus zu verstehen.					
Der Home Screen hilft mir meinen Nährstoffstatus zu verbessern.					
Der Home Screen motiviert mich meinen Ernährungsstatus zu verbessern.					
Der Home Screen verbessert meine Kenntnisse über Nahrungsmittel und enthaltene Nährstoffe.					

	Trifft überhaupt nicht zu	Trifft eher nicht zu	Teils / Teils	Trifft eher zu	Trifft voll und ganz zu
Der Home Screen motiviert mich die App häufiger zu nutzen.	☐	☐	☐	☐	☐
Ich habe Interesse daran den Home Screen häufiger zu nutzen.	☐	☐	☐	☐	☐

E2. Anmerkungen/Verbesserungsvorschläge zum Home-Screen

E3. Inwieweit treffen die folgenden Aussagen zum Nährstoffübersicht-Screen zu?

	Trifft überhaupt nicht zu	Trifft eher nicht zu	Teils / Teils	Trifft eher zu	Trifft voll und ganz zu
Ich finde die Nährstoffübersicht verständlich.	☐	☐	☐	☐	☐
Ich finde die Nährstoffübersicht informativ.	☐	☐	☐	☐	☐
Ich finde die Nährstoffübersicht ansprechend.	☐	☐	☐	☐	☐
Ich finde die Nährstoffübersicht überflüssig.	☐	☐	☐	☐	☐
Die Nährstoffübersicht hilft mir meinen persönlichen Nährstoffstatus zu verstehen.	☐	☐	☐	☐	☐
Die Nährstoffübersicht hilft mir meinen Nährstoffstatus zu verbessern.	☐	☐	☐	☐	☐
Die Nährstoffübersicht motiviert mich meinen Ernährungsstatus zu verbessern.	☐	☐	☐	☐	☐
Die Nährstoffübersicht verbessert meine Kenntnisse über Nahrungsmittel und enthaltene Nährstoffe.	☐	☐	☐	☐	☐
Die Nährstoffübersicht motiviert mich die App häufiger zu nutzen.	☐	☐	☐	☐	☐
Ich habe Interesse daran die Nährstoffübersicht häufiger zu nutzen.	☐	☐	☐	☐	☐

E4. Anmerkungen/Verbesserungsvorschläge zur Nährstoffübersicht

E5. Inwieweit treffen die folgenden Aussagen zum Nährstoffdetailansicht-Screen zu?

	Trifft überhaupt nicht zu	Trifft eher nicht zu	Teils / Teils	Trifft eher zu	Trifft voll und ganz zu
Ich finde die Nährstoffdetailansicht verständlich.	☐	☐	☐	☐	☐
Ich finde die Nährstoffdetailansicht informativ.	☐	☐	☐	☐	☐
Ich finde die Nährstoffdetailansicht ansprechend.	☐	☐	☐	☐	☐
Ich finde die Nährstoffdetailansicht überflüssig.	☐	☐	☐	☐	☐
Die Nährstoffdetailansicht hilft mir meinen persönlichen Nährstoffstatus zu verstehen.	☐	☐	☐	☐	☐
Die Nährstoffdetailansicht hilft mir meinen Nährstoffstatus zu verbessern.	☐	☐	☐	☐	☐
Die Nährstoffdetailansicht motiviert mich meinen Ernährungsstatus zu verbessern.	☐	☐	☐	☐	☐
Die Nährstoffdetailansicht verbessert meine Kenntnisse über Nahrungsmittel und enthaltene Nährstoffe.	☐	☐	☐	☐	☐
Die Nährstoffdetailansicht motiviert mich die App häufiger zu nutzen.	☐	☐	☐	☐	☐
Ich habe Interesse daran die Nährstoffdetailansicht häufiger zu nutzen.	☐	☐	☐	☐	☐

E6. Anmerkungen/Verbesserungsvorschläge zur Nährstoffdetailansicht

E7. Inwieweit treffen die folgenden Aussagen zum Screen mit dem statistischen Verlauf aller Nährstoffe zu?

	Trifft überhaupt nicht zu	Trifft eher nicht zu	Teils / Teils	Trifft eher zu	Trifft voll und ganz zu
Ich finde die Statistikansicht der Nährstoffe verständlich.					
Ich finde die Statistikansicht der Nährstoffe informativ.					
Ich finde die Statistikansicht der Nährstoffe ansprechend.					
Ich finde die Statistikansicht der Nährstoffe überflüssig.					
Die Statistikansicht der Nährstoffe hilft mir meinen persönlichen Nährstoffstatus zu verstehen.					
Die Statistikansicht der Nährstoffe hilft mir meinen Nährstoffstatus zu verbessern.					
Die Statistikansicht der Nährstoffe motiviert mich meinen Ernährungsstatus zu verbessern.					
Die Statistikansicht der Nährstoffe verbessert meine Kenntnisse über Nahrungsmittel und enthaltene Nährstoffe.					
Die Statistikansicht der Nährstoffe motiviert mich die App häufiger zu nutzen.					
Ich habe Interesse daran die Statistikansicht der Nährstoffe häufiger zu nutzen.					

E8. Anmerkungen/Verbesserungsvorschläge zur Statistikansicht der Nährstoffe

E9. Inwieweit treffen die folgenden Aussagen zum Screen mit der Nährstoffvorschau für eine bestimmte Essens-/Rezeptauswahl zu?

	Trifft überhaupt nicht zu	Trifft eher nicht zu	Teils / Teils	Trifft eher zu	Trifft voll und ganz zu
Ich finde die Nährstoffvorschau verständlich.					
Ich finde die Nährstoffvorschau informativ.					
Ich finde die Nährstoffvorschau ansprechend.					
Ich finde die Nährstoffvorschau überflüssig.					
Die Nährstoffvorschau hilft mir meinen persönlichen Nährstoffstatus zu verstehen.					
Die Nährstoffvorschau hilft mir meinen Nährstoffstatus zu verbessern.					
Die Nährstoffvorschau motiviert mich meinen Ernährungsstatus zu verbessern.					
Die Nährstoffvorschau verbessert meine Kenntnisse über Nahrungsmittel und enthaltene Nährstoffe.					
Die Nährstoffvorschau motiviert mich die App häufiger zu nutzen.					
Ich habe Interesse daran die Nährstoffvorschau häufiger zu nutzen.					

E10. Anmerkungen/Verbesserungsvorschläge zur Nährstoffvorschau

E11. Inwieweit treffen die folgenden Aussagen zum Screen mit der Nährstoffvorschau samt Nährstoffdetails für eine bestimmte Essens-/Rezeptauswahl zu?

	Trifft überhaupt nicht zu	Trifft eher nicht zu	Teils / Teils	Trifft eher zu	Trifft voll und ganz zu
Ich finde die Nährstoffvorschau samt Nährstoffdetails verständlich.					
Ich finde die Nährstoffvorschau samt Nährstoffdetails informativ.					
Ich finde die Nährstoffvorschau samt Nährstoffdetails ansprechend.					
Ich finde die Nährstoffvorschau samt Nährstoffdetails überflüssig.					
Die Nährstoffvorschau samt Nährstoffdetails hilft mir meinen persönlichen Nährstoffstatus zu verstehen.					
Die Nährstoffvorschau samt Nährstoffdetails hilft mir meinen Nährstoffstatus zu verbessern.					
Die Nährstoffvorschau samt Nährstoffdetails motiviert mich meinen Ernährungsstatus zu verbessern.					

	Trifft überhaupt nicht zu	Trifft eher nicht zu	Teils / Teils	Trifft eher zu	Trifft voll und ganz zu
Die Nährstoffvorschau samt Nährstoffdetails verbessert meine Kenntnisse über Nahrungsmittel und enthaltene Nährstoffe.	☐	☐	☐	☐	☐
Die Nährstoffvorschau samt Nährstoffdetails motiviert mich die App häufiger zu nutzen.	☐	☐	☐	☐	☐
Ich habe Interesse daran die Nährstoffvorschau samt Nährstoffdetails häufiger zu nutzen.	☐	☐	☐	☐	☐

E12. Anmerkungen/Verbesserungsvorschläge zur Nährstoffvorschau samt Nährstoffdetails

Teil F: Ernährungsumstellung

F1. Bitte geben Sie an, wie genau Sie der folgenden Aussage zustimmen / nicht zustimmen: Im Laufe der vergangenen Monate habe ich, seitdem ich Rückmeldungen zu meiner Ernährung erhalte, Änderungen...

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Teils / Teils	Stimme eher zu	Stimme voll und ganz zu
an meinem Verzehr von Vollkornnahrungsmitteln vorgenommen, z.B. Vollkornbrot, Vollkornnudeln, brauner Reis.	☐	☐	☐	☐	☐
an der Zuckermenge vorgenommen, die ich esse.	☐	☐	☐	☐	☐
an der Menge an Fett vorgenommen, die ich esse.	☐	☐	☐	☐	☐
an der Anzahl der Portionen von fettem Fisch vorgenommen, die ich in einer Woche esse, z.B. Lachs, Makrele, Sardinen, Forelle.	☐	☐	☐	☐	☐
an der Menge an Salz vorgenommen, die ich esse.	☐	☐	☐	☐	☐
an der Anzahl der Früchte vorgenommen, die ich esse.	☐	☐	☐	☐	☐
an der Menge an Gemüse vorgenommen, die ich esse.	☐	☐	☐	☐	☐
an den Portionsgrößen der Mahlzeiten und Nahrungsmittel vorgenommen, die ich esse.	☐	☐	☐	☐	☐

F2. Wenn Sie die Menge an Vollkornnahrung in Ihrer Ernährung verändert haben, welche Änderungen haben Sie vorgenommen? Bitte kreuzen Sie alle zutreffenden an:

- Verzehr von Vollkorncerealien, z.B. Branflakes. ☐
- Zugabe von Samen zu anderen Nahrungsmitteln, z.B. Cerealien / Joghurts / Salate. ☐
- Erhöhung der Menge an Vollkornbrot, die ich esse. ☐
- Ersetzung von weißem Reis durch braunen Reis. ☐
- Ersetzung von weißen Teigwaren durch Vollkornteigwaren. ☐
- Erhöhung der Portionsgrößen von Vollkornprodukten. ☐
- Sonstiges ☐

Sonstiges

F3. Wenn Sie die Zuckermenge in Ihrer Ernährung verändert haben, welche Änderungen haben Sie vorgenommen? Bitte kreuzen Sie alle zutreffenden an:

- Reduzierung der Menge an Zucker, die ich Lebensmitteln, z.B. Tee / Müsli / Brei, zugebe. ☐
- Kauf von Lebensmitteln mit "ohne Zuckerzusatz"-Kennzeichnung oder zuckerfreien Sorten. ☐
- Reduzierung der Menge an zuckerhaltigen, kohlensäurehaltigen Getränken (keine Diätgetränke), die ich konsumiere. ☐
- Verringerung der Menge an zuckerhaltigen Lebensmitteln, die ich esse (z.B. Kuchen, Gebäck). ☐
- Reduzierung meiner Portionsgrößen von zuckerhaltigen Speisen / Getränken. ☐
- Sonstiges ☐

Sonstiges

F4. Wenn Sie Änderungen an der Fettmenge in Ihrer Ernährung vorgenommen haben, welche Änderungen haben Sie vorgenommen? Bitte kreuzen Sie alle zutreffenden an:

- Reduzierung der verwendeten Fettmenge zum Kochen. ☐
- Entfernung von Haut und/oder Fett von Fleisch. ☐
- Verzehr von magereren Fleischsorten. ☐
- Verzehr von mehrfach ungesättigten und einfach ungesättigten Fetten (wie z.B. Olivenöl, Sonnenblumenöl) statt gesättigten Fetten (wie z.B. Butter, Schmalz). ☐
- Verzehr von fettarmen Sorten von Nahrungsmittelprodukten (z.B. fettreduzierte Milch / Joghurt). ☐
- Reduzierung des Verzehrs von fettreichen Snacks (z.B. Chips, Pralinen, Gebäck, Kuchen). ☐
- Reduzierung meiner Portionsgrößen von fettreichen Lebensmitteln. ☐
- Sonstiges ☐

Sonstiges

F5. Wenn Sie Änderungen an Ihrer Salzaufnahme vorgenommen haben, welche Änderungen haben Sie vorgenommen? Bitte kreuzen Sie alle zutreffenden an:

- Reduzierung der Menge an Salz, die ich während des Kochens zu den Speisen hinzufüge. ☐
- Verzicht auf Zugabe von Salz zu Lebensmitteln während des Kochens. ☐
- Reduzierung der Menge an Salz, die ich gekochten Lebensmitteln hinzufüge. ☐
- Verzicht auf Zugabe von Salz zu gekochten / zubereiteten Speisen. ☐
- Kauf von Lebensmittel, die mit "ohne Salzzusatz" gekennzeichnet sind. ☐
- Reduzierung des Verzehrs von verarbeiteten Lebensmitteln mit hohem Salzgehalt (z. Suppen, gesalzene Chips oder Nüsse, verarbeitetes Fleisch, z.B. Schinken oder Salami). ☐
- Sonstiges ☐

Sonstiges

F6. Wenn Sie Ihre Obstaufnahme verändert haben, welche Änderungen haben Sie vorgenommen? Bitte kreuzen Sie alle zutreffenden an:

- Verzehr von mehr frischem Obst. ☐
- Verzehr von mehr Trockenobst. ☐
- Verzehr von mehr Obst in Dosen. ☐
- Verzehr von mehr reinen Fruchtsäften / Smoothies. ☐
- Erhöhung meiner Portionsgrößen. ☐
- Sonstiges ☐

Sonstiges

F7. Wie viele Portionen Obst und Gemüse haben Sie an einem durchschnittlichen Tag im letzten Monat gegessen? Bitte denken Sie daran, frisches, tiefgefrorenes, getrocknetes oder konserviertes Obst oder Gemüse mit einzubeziehen. *Beispiele für jeweils eine Portion: 2 Kiwis, 1 Apfel, 1 Esslöffel Rosinen, 150 ml Glas Fruchtsaft, 3 gehäufte Esslöffel Mais oder Karotten, 3-8 Blumenkohlröschen.*

Anzahl der Portionen:

F8. Bitte geben Sie im folgenden Feld alle anderen Änderungen an, die Sie im Laufe des letzten Monats an Ihrer Ernährung vorgenommen haben, seit Sie Ihre Rückmeldungen zu Ihrer Ernährung erhalten.

Teil G: Kochverhalten

G1. Wie kochen Sie im Moment? (Alle zutreffenden Optionen ankreuzen)

- Fertige Zutaten zu einer kompletten Mahlzeit zusammenstellen (z. B. fertige Soßen). ☐
- Fertiggerichte kochen. ☐
- Zubereitung von Gerichten aus Grundzutaten. ☐
- Ich koche gar nicht. ☐

G2. Wie oft bereiten Sie in einer normalen Woche eine Hauptmahlzeit aus Grundzutaten zu?

- Täglich ☐
- 4-6 mal pro Woche ☐
- 2-3 mal pro Woche ☐
- Einmal pro Woche ☐
- Weniger als einmal pro Woche ☐
- Niemals ☐

G3. Wie zuversichtlich fühlen Sie sich...?

	Überhaupt nicht zuversichtlich	Eher nicht zuversichtlich	Teils / Teils	Eher zuversichtlich	Sehr zuversichtlich
... aus Grundzutaten kochen zu können?					
... nach einem einfachen Rezept zu kochen?					
... Speisen zu essen, die Sie noch nie gegessen haben?					
... neue Speisen und Rezepte zu kochen?					

Teil H: Person

H1. Fragen zum Verhalten

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Teils / Teils	Stimme eher zu	Stimme voll und ganz zu
Wenn mir ein Familienmitglied einen Gefallen tut, bin ich sehr geneigt, diesen Gefallen zu erwidern.	☐	☐	☐	☐	☐
Ich erwidere Gefallen immer.	☐	☐	☐	☐	☐
Ich glaube, dass seltene Produkte wertvoller sind als Massenprodukte.	☐	☐	☐	☐	☐
Wenn mein Lieblingsgeschäft kurz vor dem Schließen steht, würde ich es besuchen, da es meine letzte Chance ist.	☐	☐	☐	☐	☐
Ich folge immer dem Rat meines Hausarztes.	☐	☐	☐	☐	☐
Wenn ein Professor mir etwas sagt, neige ich dazu zu glauben, dass es wahr ist.	☐	☐	☐	☐	☐
Immer wenn ich mich zu einem Termin verpflichte, mache ich das, was ich gesagt habe.	☐	☐	☐	☐	☐
Ich versuche alles zu tun, was ich versprochen habe.	☐	☐	☐	☐	☐
Wenn jemand aus meinem sozialen Netzwerk mich über ein gutes Buch informiert, neige ich dazu, es zu lesen.	☐	☐	☐	☐	☐
Wenn ich in einer neuen Situation bin, sehe ich andere an, um zu sehen, was ich tun soll.	☐	☐	☐	☐	☐
Ich akzeptiere Ratschläge von meinem sozialen Netzwerk.	☐	☐	☐	☐	☐
Wenn ich jemanden mag, bin ich eher geneigt, ihm oder ihr zu glauben.	☐	☐	☐	☐	☐

H2. Fragen zu Charakterzügen

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Teils / Teils	Stimme eher zu	Stimme voll und ganz zu
Ich bin eher zurückhaltend, reserviert.	☐	☐	☐	☐	☐
Ich schenke anderen leicht Vertrauen, glaube an das Gute im Menschen.	☐	☐	☐	☐	☐
Ich bin bequem, neige zur Faulheit.	☐	☐	☐	☐	☐
Ich bin entspannt, lasse mich durch Stress nicht aus der Ruhe bringen.	☐	☐	☐	☐	☐
Ich habe nur wenig künstlerisches Interesse.	☐	☐	☐	☐	☐
ch gehe aus mir heraus, bin gesellig.	☐	☐	☐	☐	☐
Ich neige dazu, andere zu kritisieren.	☐	☐	☐	☐	☐
Ich erledige Aufgaben gründlich.	☐	☐	☐	☐	☐

	Stimme überhaupt nicht zu	Stimme eher nicht zu	Teils / Teils	Stimme eher zu	Stimme voll und ganz zu
Ich werde leicht nervös und unsicher.	☐	☐	☐	☐	☐
Ich habe eine aktive Vorstellungskraft, bin fantasievoll.	☐	☐	☐	☐	☐

Teil I: Allgemeines Feedback

I1. Fragen, Anmerkungen, Wünsche...

H

INDUCTIVE AND DEDUCTIVE CODING OF INTERVIEW DATA

The following table gives an exemplary sentence for each of the coded concepts in the qualitative analysis in chapter 10. The first column names the general topic of investigation. The second column states the question asked during the interview. The third column shows the label applied in the first deductive coding pass and the fourth column shows the more specific subcategory after the inductive coding pass. Finally, the last column shows the example sentence from the interview (in German).

Theme	Question	Deductive	Inductive	Example Sentence
Eating Motives	Tell us why you eat	Hunger	Hunger	Aber ich esse meistens, weil ich halt Hunger habe.
		Appetite	Appetite	Ähm, ja natürlich, weil es schmeckt, sag ich jetzt mal.
		Health	Health	...wenn es mir selber gut geht, dann kann ich auch auf mich aufpassen. Dann ernähre ich mich auch gut.
			Survival	Warum ich esse? Ja damit ich am Leben bleibe!
		Weight	Appearance	Ähm ich muss dazu sagen, ich bin auch ein bisschen Eitel und ich habe ein gewisses Alter und ja, da muss man halt ein bisschen mehr aufpassen.
		SocialNorms	-	
		Image	Tradition	Ich stamme aus einem kleinen Bauernhof und bei uns gab es immer ursprüngliches Essen. Also das heißt keine Fertigprodukte, sondern es wurde täglich gekocht. Und das mache ich auch heute noch so
		Emotion	Stress	Unter Stress, hm ah, wenn ich unter Stress bin, dann esse ich normalerweise mehr, als sonst.
		SocialFactors	Family	ich habe kleine Kinder, ... Um das umzusetzen und ähm, ist halt auch nicht so das Interesse zweierlei Sachen zu zu bereiten. // Ähm, ja mein Mann ist ein bisschen empfindlich, was seinen Darmtrakt angeht und wenn ich selbst koche, ohne Fertigprodukte, oder irgendwelche Zusätze, dann geht es ihm besser.
			SocialFactors	Also was sehr stark ein Motivator ist, ist wenn man sich mit Leuten trifft, dann isst man zusammen, das ist klar.
		Habit	Habit	Esse so zu sagen nach festen Zeiten und manchmal habe ich da zufällig auch Hunger.
		Simplicity	Time	Also dadurch, dass ich Teilzeit arbeite und ähm vier Mal die Woche Teilzeit bis mittags, mal früher, mal später nach Hause komme, hängt natürlich auch davon ab, ob ich dann mittags ähm, großartig was esse. Ob noch was da ist vom Vortag, was ich warm mache. Ob ich die Mittagszeit, die ich dann habe nutze, um Besorgungen zu machen, oder den Haushalt zu machen, bevor meine Kinder nach Hause kommen. Ähm, also das ist sicherlich ein starker Einflussfaktor, meine Arbeit. // zwischendurch mal welche Pommes, wenn es auch mal so schneller geht.
	Tell us how your perception of eating has changed	Pleasure	Pleasure	Ähm, na ja, irgendwo ist es natürlich eine Befriedigung, wenn man sich, vor allem wenn es eine stressige Fahrt ist und man eine Pause hat und sich was gönnt
			Regret	Und dann vor allem wenn ich dann weiß, eigentlich tut sie mir nicht gut die Schokolade, aber dann habe ich sie trotzdem gegessen. Und danach hat es mir nicht mehr Spaß gemacht. Währenddessen vielleicht schon. ... Am nächsten Tag dann vielleicht nicht mehr, so. Also das schlechte Gewissen kam dann schon auch irgendwie.
			NoConstraints	Und da tu ich mich natürlich ein bisschen leichter, als andere Personen, die Heißhunger auf Süßes haben.
		Fun	EffortTracking	Also mich stresst halt dieses abends alles eintragen in dieses Ernährungstagebuch. Das ist für mich also ein riesiger Aufwand immer gewesen. Und dann habe ich schon, äh, manchmal gedacht ich esse mal lieber nichts, dann muss ich nichts eintragen, so ungefähr.
		Social Behaviour	SocialBehaviour	Ähm und zu Hause, dann eher am Wochenende esse ich zusammen mit meinem Partner und wir kochen abwechselnd. Also es hat sich eigentlich nichts geändert.
		Planning	-	
		Consciousness	Weight	Jetzt nicht, ich hätte mir gewünscht, dass ich mehr abnehme. Das war jetzt gar nicht so der große Effekt, aber das war dann irgendwann gar nicht mehr so wichtig. Ist eben einfach ich fühle mich, einfach mental, dass ich Power habe. ... Das fand ich dann irgendwann viel wichtiger.
			FoodItems	Also, dass ich dann etwas ausgetauscht habe. Äh ja, man hat ja gesehen, wo es fehlt, wo halt irgendwie was verbessert werden kann und da hab ich halt, das habe ich dann in Ansätzen schon so probiert.
			Calories	Die Kalorienanzeige hat mich sowohl positiv, als auch negativ überrascht.
			Nutrients	Ähm, also teilweise war es eine gute Motivation. Ähm, was ich auch im Fragebogen beantwortet habe, die Statistik zum Beispiel, die Übersicht. Das man dann ähm, eine Auslagerung hatte, oh ja ich brauche eher die Nährstoffe, weil ich die vernachlässigt habe.
			Portions	Ni, dass man da irgendwie, was überhaupt so Größenordnungen sind so einzelne. Ähm, dafür vielleicht einen Blick kriegt und denkt, es geht auch ein bisschen weniger.

Theme	Question	Deductive	Inductive	Example Sentence
Dietary Change	Tell us how you changed your nutrition	FoodItems	Vegan	Ähm meistens versuch ich jetzt mit dem veganen, wähle ein bisschen mehr vegan zu essen.
			Vegetables	ja Gemüse, ha, je nachdem wie das
			Nuts	Dass ich zum Beispiel Nüsse jetzt viel öfter, mal einbaue. Vitamin D, oder Calcium viel mehr aufpasse.
			Fruit	Ich hab immer nur geguckt was für Nährstoffe jetzt gefehlt haben und wenn jetzt mal irgendwie Orange da stand, hab ich mal noch eine Orange gegessen.
			Fibre	ist immer sehr unterschiedlich, weiß ich ja auch nicht genau Salat und versuch wirklich Ballast zu mir zu nehmen
		-	Salt	Mal so wirklich in welchem Bereich liegen denn so meine Nährstoffe und so. Wo kann ich, wo hab ich im Prinzip, zum Beispiel bei Salz. Ich salze nicht extrem, aber da hab ich kaum eine Chance so viel nach zu steuern, dass ich da wirklich in den besseren Bereich käme.
		-	Sugar	Und dann habe ich tatsächlich mal auf Zucker verzichtet.
		-	Carbohydrates	Ähm, ein bisschen anders so gegessen, also mein Essen war eher so ein bisschen kohlenhydratlastig, also viel Brot und Kartoffeln und Nudeln und so Zeug.
		-	FattyAcids	Ähm vielleicht noch bei den Fetten noch mehr die Unterschiede bei den einfach und mehrfach gesättigten Fettsäuren. Und auch beim Käse mit dem äh, Fettgehalt.
		-	TraceElements	Ich muss sagen in erster Linie die Nährstoffzusammensetzung, speziell die Spurenelemente.
		Portions	LessPortions	Ja, ich habe versucht, ähm, ein bisschen weniger zu essen.
			Balanced	So eine regelmäßigere, ausgewogene Ernährung lerne.
		-	NoChange	Mh, ne also eigentlich, also weil ich hab das nicht recht. Ich mach nicht bei der Studie mit, um mein Essverhalten zu ändern. Mich interessiert es einfach wie es so ist, aber nicht, weil ich was ändern will, oder ja. Einfach aus Interesse eigentlich. Deshalb, ja.
		PointsInTime	Hunger	Und das war gut, seitdem konnte ich das jetzt viel besser, dass ich das Essen einteile, weil ich am Tag und am Abend dann nicht so völlig ausgehungert war, ähm das war, das war vielleicht so der größte Benefit den ich hatte in der Zeit.// Ich möchte äh, äh, so so Maß finden, was ich eben kann und äh ich möchte einfach für jede Mahlzeit Hunger bekommen. Ja richtigen wahren Hunger, dass der Magen knurrt.
	Tell us how you will sustain your changes	Difficulties	Effort	Hm ja, ich denke schon, dass ich da immer mal wieder rückfällig werde und es ist dann aber, es ist so ein Effekt von Stress, oder Zeitmangel.
			Helplessness	Und ähm, das war ein bisschen schwierig muss ich sagen, weil ähm häufig die Nährstoffbilanz, dann nicht gestimmt hat. Da war irgendwas defizitär. Und beim Versuch das aufzuholen, das ist fast unmöglich, also wenn man quasi über den Tag mal bis zum Mittagessen ein Defizit eingefahren hat, dann ist es vorbei.
			NoDifficulties	Ne, ne also gar nicht. Ich hab jetzt auch nichts gegessen, was ich sonst nicht essen würde, sondern man kam dann eher nochmal auf die Idee, das dann wirklich nochmal zu essen.
		Relapse	SocialFactors	Aber es gibt so Sachen, was meine Kinder gar nicht essen, äh und dann kann ich das auch nicht kochen.
			Restaurant	Wenn ich irgendwo beim Chinesen was kaufe, dann weiß ich nicht ob der in sein Essen einen Teelöffel Zucker rein gemacht hat, aber ähm bin ich mir bewusst, dass ich keinen Fruchtjoghurt kaufe, sondern meinen Joghurt selber mache mit Obst und so.
			FavoriteFood	Ja ich versuche schon gesund zu essen, aber, das klappt leider nicht immer. Mal ein Keks kommt immer wieder dazwischen. Ähm, Bier auch. Mal Schokolade. Ja, hm. Sehr viele Teigsachen, hm, sehr viele Schokoladen, leider.
			Illness	Davor hatte ich so eine Woche ein bisschen äh Magen-Darm-Grippe. Da war das alles mit Essen sowieso nicht einfach zu koordinieren, aber wenn ich jetzt demnächst mich mal wieder frage, was könnte ich denn als nächstes kochen, könnte ich mir auf jeden Fall vorstellen, dass ich rein gucke.
			Holiday	Aber ich hab dann schon mal so weiter durchgeblättert und also grad so für den Obstsalat hab ich mich da so ein bisschen Inspiration geholt und ansonsten ähm, wie, wie gesagt ich war jetzt grad einfach eine Woche im Urlaub.
			Work	Natürlich, wenn ich arbeiten gehe brauche ich mehr. Das weiß ich auch. Ich esse mehr, wenn ich zu Hause bin, dann ist es deutlich weniger, was ich äh essen wollte.
			Weekend	Ja es hat sich schon so ein Muster, also am Wochenende, da schlägt man immer etwas über die Strenge. ... Und unter der Woche pendelt sich das dann wieder so ein bisschen ein.
			Events	Und bis Ostern nehme ich es mir auf jeden Fall vor. Ähm also, ja ich kann natürlich das nicht immer einsehen.
		PermanentChanges	KnowledgeGain	
			Reduction	
			NewHabits	Ähm, also, ja soweit es geht konnte ich es kontrollieren. Und ich habe das jetzt durchgezogen genau.

Theme	Question	Deductive	Inductive	Example Sentence
Interactions	Tell us how you mostly used Nutrilize	Fucntionality	Statistics	Bei dieser Statistik hab ich dann alles so nachgeguckt, wie es so ist. ... Hm, also ich find?s total interessant, was man da so mitkriegt.
			HomeScreen	Also es war nicht schlecht, da stand ja dann auch immer da, also in dem Bereich solltest ein bisschen mehr essen, da brauche ich mehr Calcium, oder dieses und jenes. Also da hat man sich dann auch gefreut, wenn sich das so vielleicht von rot auf gelb geändert hat.
			Tracking	Also ich würde sagen, bisher nutze ich die App eher so, für das Eintragen.
			Calories	Und den Rest finde ich schon ganz interessant, dass man halt sieht, äh, wie viele Kalorien man jetzt noch übrig hat in Anführungsstrichen für den restlichen Tag, oder auch nicht.
			InformAboutFoodItems	Also ich habe mich informiert ähm, also nicht nur über die einzelnen Lebensmittel, sondern wie gesagt auch so diese ganzen Gruppen.
		Timing	AfterMeal	Direkt, direkt, meistens direkt. Entweder, meistens nach dem Essen was ich alles gegessen habe, hab ich direkt eingetragen, ohne zu lügen.
			MoreInBeginning	Ähm und dann, ähm, war es sehr spannend am Anfang, sie zu erkennen, sie kennenzulernen und dann hab ich am meisten benutzt. Und in letzter Zeit, ähm, hat sich etwas berufliches bei mir geändert und auf Grund dessen, konnte ich leider nicht so viel darauf aufpassen, dass ich meine Einträge mache.
			IfTime	Weil während dem kochen hab ich schon am Anfang gemerkt, dass das doch ein bisschen aufwendig ist, dass man immer alles aufschreiben muss. Und deshalb hab ich mir immer alles per Hand aufgeschrieben, dann in die App geschrieben, also wenn ich mal Zeit hatte, hab ich mal geguckt wie so die letzten Jah- äh Tage waren.
			InTheEvening	Also ähm, bei mir war ja das Problem, dass es auf meinem Handy gar nicht lief. Ich musste das über meines Sohnes Handy laufen lassen. Und den dann immer abends dazu zu bringen mir das Handy zu geben, dass ich das eintrage war schwierig.
			BeforeMeal	Also meistens habe ich es abends angemacht um das einzutragen, aber auch teilweise zwischendrin, um zu gucken was kann ich mir jetzt kochen. Oder was kann ich machen, oder was tut mir jetzt gut?
			AddLaterOn	Hatte die letzten Tage so privat auch noch ein paar Schwierigkeiten mit unserem Sohn, da habe ich dann auch einmal zwei Tage nachgetragen.
		Motives	-	-
	Tell us which functions influenced your diet	Planning	PlanningNutrientInfos	Und am Abend habe ich mir dann immer noch, ja je nachdem wie die Rechnung stattgefunden hat, nochmal nachgeschaut, wo da die Mangelnährstoffe sind. Und habe dann für den nächsten Tag gesagt, ach komm, wenn es in der Kantine jetzt einen Fisch gibt, dann esse ich einen Fisch.
		DecisionMaking	DecisionRecommendations	Gut, wenn ich jetzt mittags überlegt habe, was koche ich, oder so, oder Frühstück, da habe ich schon mal rein geguckt, um zu gucken, was sie mir vorschlagen dann da.
			DecisionCalories	Und dann gebe ich das zum Beispiel auch schon mittags ein, dann weiß ich, ja ähm drei Scheiben Brot und was da drauf ist und das ist ganz lustig, weil dann sehe ich, ah ich habe ja noch 200 Kalorien übrig, dann kann ich ja heute Mittag noch einen Latte Macchiato trinken.
		Feedback	FeedbackHomeScreen	Ähm ja das, also ich habe eigentlich jetzt immer jeden Tag in der Frühe darauf geschaut. Was ist jetzt quasi, noch, na also diese Übersicht auf der Hauptseite. ... Was ist jetzt da, ähm, also bei mir sind jetzt immer rote Pfeile nach unten gewesen, oder nach oben.
			FeedbackDiary	Ni, das ist so, dass man dann vielleicht nochmal sein Verhalten überdenkt und vielleicht auch ändert. Aber so eine App erst mal ist ja sehr eigenverantwortlich zu bedienen und da muss jeder sehen, was er da draus macht letztendlich.
			FeedbackFoodItems	Also das ist, das ist interessant. Ja sehen, was jetzt da so. Also ein Stück Kuchen so, wie, wie hoch ist denn dann äh, ähm Kalorien, ni.
			FeedbackStatistics	Und meine Statistik eben überall super war. Ja das fand ich eben einfach gut. Deswegen, das war so, ein bisschen war das wie so ein Spiel, aber das hatte natürlich Auswirkungen auf das reale Leben.

Theme	Question	Deductive	Inductive	Example Sentence
	Tell us about difficulties with Nutrilize	Technical	ChangePassword	Und das hat nicht geklappt, ähm, später mit dem einloggen, denn ich hab komischerweise den Benutzernamen auch geändert und Passwort geändert. Dann bin ich nicht mehr rein gekommen, dann bin ich auf Sie zurück gekommen, Sie haben mich freigeschaltet.
			Logout	Und was mir auch noch aufgefallen ist, sie hat mich manchmal einfach raus geschmissen. Ich weiß jetzt nicht, ob das an meinem Handy lag, oder an der App.
			TooSlow	Also jetzt weiß ich auch nicht, ob ich das noch weiter mache. Das war dann, hat dann ewige Zeit gedauert, bis man das Essen da eingetragen hatte.
			ErrorsAndCrashes	Ähm dann kamen immer irgendwelche Fehlermeldungen. Und da hast du dann schon ein bisschen die Lust verloren.
			Internet	Ähm, dann hat die am Anfang, ähm, also ich weiß nicht, ob es an unserem Internet hier lag, oder insgesamt an der App. Dann hat die ewig gebraucht bis die die Sachen dann aufgenommen hat, bis die das eingetragen hat.
			ScreenTooSmall	Da hätte ich mir manchmal fast gewünscht, dass man da irgendwie auch ein Programm ganz normal am Computer öffnen könnte. ... Weil du da einfacher da nach gucken könntest. Da könntest du irgendwie mal eine Übersicht, sage ich jetzt mal öffnen, und dann steht halt drin, äh, hier sind die Hauptgerichte, die empfehlenswert wären. Dann hätte man halt eine breitere, ja auch dadurch, dass der Bildschirm schon einfach größer ist, könnte man sich das glaube ich ein bisschen übersichtlicher anschauen, als so jetzt auf dem Handy.
			BarcodeScanning	Und was auch nicht gut funktioniert hat, aber vielleicht war ich da bloß ein bisschen zu ungeschickt, dieses Barcode scannen ... Das hat er dann, da hat er nichts gefunden. ... Also vielleicht habe ich exotische Marken, das weiß ich nicht. Aber es hat nicht gut funktioniert.
		Understanding	NegativeNutritionWhenLittleInput	Dann irgendwann hab ich wenig reingetragen, oder gar nichts eingetragen. Da war fünf von 27 Optimisierung. Da die Ernährung nicht so gut ausgefallen ist. ... Und, ähm, das hat mich verunsichert und dann hab ich ähm, nach einiger Zeit gar nichts mehr eintragen können.
			RecommendationIllogical	Zum Beispiel, dass mir dann für ein Mittagessen angezeigt wurde, ähm, kam glaube ich jedes Mal Balsamicokonzentrat, das war jetzt keine naheliegende Idee, Balsamicokonzentrat zum Mittagessen zu essen. ... Oder das, genau das ist jetzt ein gutes Beispiel dafür. Ich verstehe das natürlich, das als Vorschlag, das wäre eine gute Salatsoße für dich. Der Inhalt aber, ja so.
			RecommendationPortionsIllogical	Ja. Genau, das 200-fache dieser Menge essen, ja um Gottes Willen.
			NutritionVeryNegative	Also das hat mich dann schon ein bisschen gewundert, dass von diesen quasi 25 Gruppen, da zum Teil bloß 15 im optimalen Bereich waren. Die da angegeben waren.
			NutritionFeedbackNotUnderstood	Meine Mangelerscheinung, oder Folat, oder so und ich habe dann Nährstoffe wo Folat und Retinol drin ist angeklickt, dann war das teilweise trotzdem ein rotes Ausrufezeichen, weil da so viel drin ist. Und da hätte die App eigentlich angepasst werden müssen. Und mir sagen müssen, es ist grün in dem Moment.
			PersonalizationNotUnderstood	Und da hatte ich aber gedacht, dass da vielleicht irgendwie dann Input kommt, dass mir dann jemand sagt, tu doch mal in dein Müsli in das eben auch Sonnenblumenkerne rein, anstatt immer nur Haferflocken, oder. Äh, da habe ich halt so gedacht, weil jetzt ist es im Moment so, dass ich eigentlich mit meinem Frühstück an und für sich zufrieden bin.
			LearnPortionSizes	Was weiß ich, Banane 170 Gramm. Da hätte ich gedacht, dass vielleicht so ein Lerneffekt mit eintritt. Dass wenn ich halt dann irgendwie fünf mal hintereinander eingegeben habe, dass ich immer 70 Gramm Banane esse.
			NutrientsNotFound	Und was ich auch schade finde, ähm, dass ich ja jetzt auch nie feststellen kann, wie viele Kalorien hat denn jetzt die Banane gehabt? Weil ich sehe ja dann eigentlich immer nur die Gesamtmenge. Was weiß ich, wenn ich jetzt anfange. Ich habe gefrühstückt, dann kann ich ja in diese Liste gehen und dann steht da dort, sie haben heute schon 460 Kalorien zu sich genommen. Aber da sehe ich ja jetzt auch nie, ähm, was ist jetzt da besonders kalorienreich, oder besonders kalorienarm gewesen, von dem was ich gegessen habe.
			WeightTrackingNotFound	lso das war dann, also sozusagen es war nett zu wissen, ich konnte immer nachschauen wie groß ich bin, aber es hatte sich nichts geändert an der Größe. Aber ich habe gedacht man könnte so eine Kurve, so eine Verlaufskurve dann entwickeln.
			SportCaloriesNotUnderstood	Da hatte ich dann auf ein mal 1700 was weiß ich, ni. Zum Beispiel. ... Am Anfang hat das funktioniert, da ähm das ist, da hat dann da angezeigt. Das war halt dann im minus, was ich Kalorien übrig hatte. Aber die letzten Tage waren es immer irgendwie mehr.
		Content	FoodItemsNotFound	Hm ja und bei vegan, grade bei vegan war so, der, der Mode ist, das habe ich nicht so alles ganz viel gekriegt. Damit Mandel-, Mandelmus, oder eine Joghurtsoße. Das hat mir ein bisschen gefehlt.
			TrackingEffort	Hm zum Beispiel, wenn ich in der Gastronomie gegessen habe, da ähm, war es zum Teil schwierig, da einzugeben, was ich täglich gegessen habe. Aber das verstehe ich auch, weil so Restaurant, von Restaurant zu Restaurant gibt?s auch Unterschiede und ähm, nicht alle Mahlzeiten werden da eingetragen. Das hatte ich schwierig gefunden. ... Wirklich alles aufzuschreiben, was ich zu mir genommen habe, wenn ich draußen gegessen habe. Ansonsten ähm, ja ähm war das ziemlich okay.
			SportItemsNotFound	Oder auch die, die sportlichen Aktivitäten, da die Tätigkeiten, die man da so eintragen kann. Also da habe ich jetzt mit Überraschung heraus gefunden, ach das gibt es ja doch.
			RecipesNotFound	Und was bei mir auch überhaupt nicht funktioniert ist, dass man diese Rezepte anguckt. ... Weil wenn du das dann wirklich dann da öffnest, gut dann es gibt vielleicht auch Rezepte, die sich so da mit dem Handy ganz praktisch öffnen lassen.

Theme	Question	Deductive	Inductive	Example Sentence
	Tell us about you usage of the visualizations	Understanding	Understood	Ja, ja. Das war sehr gut. Also man weiß zum Beispiel, Folat, ich hab zu wenig gegessen. Man schaut was man, äh, welche Lebensmittel erhält, erhalten diesen Folat und dann kann man zusätzlich, also das essen.
			Confused	Ähm, ja, also was ich irritierend fand, ist die Farbe der Kreise. Weil es wirklich nichts zu tun hat mit dem, was für mich jetzt in meiner Ernährung wichtig ist.
		Helpfullness	HelpfulFeedback	Also da gucke ich dann lieber da auf das Bild und da steht deutlich, ich bin da im grünen Bereich, wunderbar. Ob ich da jetzt 50 Milligramm zu mir genommen habe, oder, das finde ich wäre jetzt nur so ein Teilwert. Da hilft mir die Grafik mehr.
			HelpfulInfos	Und auch dass da nochmal detailliert aufgelistet war, ich komme wieder auf die Fette zurück, äh, mit einfach, oder mehrfach gesättigte und ungesättigte, dass das auch nochmal erklärt war
			HelpfulFoodItems	Dann hat man erklärt bekommen wozu das gut ist. Und ja wo es drin ist uns so was man essen könnte. Das fand ich eigentlich ganz gut.
		Appealing	Appealing	Ja was soll ich denn da sagen, das war doch schön. Das war gut.
		-	HomeScreen	Also da, das fand ich immer sehr, sehr hilfreich. Die gleich bei der Homepage erschienen sind, wo die grobe Statistik mal da war und zumindest mal die Aufreißer im negativen und im positiven Feld waren.
		-	WhatIf	Ähm, und genauso auch bei den Rezepten, also bei den einzelnen Rezepten hat es das auch gegeben. Also diese roten, grünen und so ähnlichen Dinger, äh, wo man dann eben sehen konnte, den nicht, da sind zu viel ungesättigte Fettsäuren, oder zu viel Zucker, oder was weiß ich. Das fand ich ganz gut.
		-	Demotivating	Genau, das waren immer die, ich sage mal, die sechs schlechtesten. ... Ist natürlich etwas frustrierend, aber ähm, dafür weiß man dann wo man dran ist. ... Ja, ja wobei es gar nicht so schlimm war. Ich habe sogar einmal einen grünen gehabt. Man glaubt es nicht.
	Tell us about your usage of the recommendations	Cooked	Cooked	Ich habe da rein geschaut und ähm, habe da zwei, drei Rezepte draus gemacht.
			GarnichtKochen	Nein, nein, nein, überhaupt nicht. Aber ich habe so meine Vorstellungen von dem was ich koche.
			InspiredCooking	Zwei, drei vier Sachen vielleicht mal ausprobiert und ich habe dann gesehen, dass viel mit Kartoffeln war. Dann dacht? ich ah, da nehme ich mal was mit Kartoffeln. So Ideen hat man dann schon bekommen.
		Health	WrongPortionSizes	Bloß die Mengenangaben. Entweder habe ich es nicht geblickt, oder war das irgendwie ganz komisch. Sie sollte die anderthalbfache Menge essen und dann kam da was weiß ich, 500 Gramm Joghurt. Naturjoghurt, dann sage ich, ich kann doch keine 500 Gramm Joghurt auf einmal essen, also.
			NotUnderstood	Ansonsten soll ich immer Flammkuchen-Rollen essen, oder so was. Das hab ich jetzt noch nicht gemacht, weil das versteh ich auch nicht ganz, warum, ich glaub es geht um eine Vitamin A Geschichte.
			StrangeRecipes	Mittags massenhaft Süßigkeiten und abends hat er wieder vorgeschlagen 400 Gramm Karamell. Oder ein anderes Mal, das war dann auch sehr nett. Da stand dann als Vorschlag für das Abendessen Kräutersalz.
		-	NoDiversity	Also die Reihenfolge der Rezepte war immer gleich. Die ersten zehn kannte ich dann schon auswendig und ähm ich hätte, ja.
		-	TechnicalProblems	Es war nicht mal so, es wäre wahrscheinlich vielseitiger gewesen, wenn ich dann runter gescrollt hätte, aber wie gesagt, das hat ja nicht immer funktioniert. Und deswegen habe ich es dann auch bleiben lassen. Die Geduld verloren.
		-	ExternalCircumstances	Es aber auch ähm, ich sag mal im äh, wie soll ich sagen, also aus meinem, ich habe kleine Kinder, ähm ich arbeite Teilzeit, es macht manches schwieriger.
		Taste	Fitting	Also ich glaube, die haben sich da dann schon ein bisschen an meinen Essgewohnheiten da angelehnt. Also, da sind dann immer Vorschläge gekommen, die eigentlich für mich passen. Also ich habe mir das so überlegt. Ja die haben das bestimmt durch das was ich eingegeben habe gesehen, die mag das und das und das, und dann kam dann entsprechend auch Vorschläge.
			NotAppealing	Da war nicht überall ein Bild dabei. Das hat mir nicht so gut gefallen. Dass kein Bild dabei war, vielleicht wäre das ein, ähm, Punkt, was man verbessern könnte.
			NotFitting	Ansonsten von den Empfehlungen fand ich das gut, allerdings nicht vegan.

Theme	Question	Deductive	Inductive	Example Sentence
OtherApps	Tell us about previous experience with nutrition apps	Tested	OtherApp	Ähm, andere App, ja tatsächlich hab ich eine, kleinen Moment, muss ich nochmal überlegen, das war eine App, die ich schon mal benutzt habe. Dafür hab ich Erfahrung mit solchen Apps und habe ähm, Interesse daran weiterhin zu benutzen. Ja das war das myfitnesspal.
		-	SearchedFor	Ich habe schon mal überlegt, ob ich gucken soll mal im Internet irgendwo. Ja ob ich da was vergleichbares finde, ja.
		UsedLongTerm	-	
		StoppedUsing	TooLittleTime	Meine berufliche Situation hat sich geändert und dann nach einiger Zeit Eintragungen, war es mir umständlich jeden Tag einzutragen, was ich gegessen habe und was ich mir alles, beim kochen musste ich aufschreiben, so viele Zwiebeln genommen, so viele Paprika genommen. Da ist es echt umständlich, ähm, das sich alles einzugeben.
		TrackedManually	Manually	Eben nicht mit einer App, aber ich habe mal bei Pfunde-AOK so ein Programm mitgemacht.
		-	NotAtAll	Ne, das eigentlich nicht. Also hab ich noch nie, so, so konkret aufgeschrieben, was ich gegessen hab. Hab ich eigentlich noch nie.
		-	Internet	Handy mit Internet hat man auch immer, da kann man mal schnell nachschauen. Wenn man wirklich irgendwas isst, wo man sich jetzt überhaupt nicht auskennt.
	Tell us about (dis)advantages of Nutrilize compared to other apps	Missing	MissingWeightTracking	Das was man immer bei myfitnesspal machen konnte. Da hat man jeden Tag Gewicht eintragen können und ich denke auch, sogar die Fettmasse.
			MissingPhysicalActivity	Ja kurz, ja also da muss man, sagen wir mal, ich lasse jetzt mal Funktionalität außen vor. Die ist natürlich noch einmal mehr auf die sportliche Betätigung auch getrimmt. Ähm, wobei ich da jetzt auch immer Probleme habe, dass wenn man da Sport eingibt, ähm, dann rechnet der Kalorien oben drauf und das finde ich macht es verhältnismäßig ungenau. Weil einfach beim Sport jeder unterschiedlich verbrennt. Wenn ich jetzt mal anderthalb Stunden Rad gefahren bin, dann zeigt mein Tacho ja auch einen anderen Kalorienverbrauch an. Aber ob der dann so genau ist, ja das ist manchmal doch fragwürdig.
			MissingBarcodeScanning	Also mir hat allerdings eine Freundin erzählt, weil ich ihr eben auch erzählt habe von dem Projekt, da hat sie gemeint Sie hatte schon mal eine App, da konntest du auch den Barcode sogar damit einscannen. Und da hat sie halt gesagt, du hasst jetzt zum Beispiel vier Stückchen Ritter Sport Nussnougat zu dir genommen.
			MissingDesign	Vielleicht so ein bisschen das, äh, Layout. Ja das ist halt die Frage. Muss es anschaulicher sein, oder nicht? Das ist halt relativ nüchtern sag ich mal. Das ganze wie?s dargestellt ist. Aber die Frage ist, braucht man das wirklich? Ist das so wichtig? Ni, also das ist halt so, dass man das ganze aufhübschen könnte, um es dadurch irgendwie ansprechender zu machen.
			MissingNutrientFoodItemRecommendation	Das hätte ich nur gerne ein bisschen aufgeklärt gehabt. Diese Funktion, dass was weiß ich, wenn da angegeben wird, Vitamin A ist jetzt zu wenig, dass man das anklickt und dann kriegt man dieses Vitamin schön dargestellt und hat dann unten so Empfehlungen, die ähm, sehr dünn sind. Da waren oft nur so drei Begriffe, oder so. Wenn man das so ein bisschen aufblasen könnte.
		Having	HavingNutrientOptimization	Hm, also diese Optimierung hat mir sehr gut gefallen, weil ich das bei den anderen Apps nicht gefunden habe bis jetzt. Wie zum Beispiel myfitnesspal.
			HavingRecipeRecommendation	Auch mit den Rezeptvorschlägen, obwohl ich das nicht gemacht habe. Und mit den Empfehlungen. Am auf Grund dessen, dass ich jetzt versucht habe, ähm, vegan zu essen, ähm, das ist der Grund, weswegen ich nicht benutzt habe. Ansonsten habe ich nur ganz, ganz positiv entgegengenommen.
			HavingStatistics	Und ich suche mal schon. Deswegen weiß ich also grade diese Statistikfunktion, die hier dabei ist, die finde ich bei keiner anderen App
			HavingSportsTracking	was ich hier jetzt ganz gut zum Beispiel fand, waren die Bewegungseinheiten, da hab ich mich schon wieder gefunden. Das ist bei anderen manchmal schwierig einzuschätzen, was die Bewegung ausmacht, die man macht.
			HavingDetailledTracking	Bekannt vor. Ja, aber das ist so ein bisschen, dass die ähm, Nahrungsmitteleingabe das ist umständlicher. Genau das ist bei Ihnen auch, diese, sage ich mal, Detailfunktionalitäten, das ist sehr modern und das finde ich gut so. Das hat diese andere App zum Beispiel nicht. Wollte ich auch noch heraus stellen. Also, dass man was eingibt und dann erscheinen gleich so Vorschläge.
		PayMore	-	
		Equal	EqualTracking	Ahm, bei myfitnesspal war, ähm, das so, dass ich ähm, genauso wie in Nutrilize die Sachen finden konnte, die ich brauchte. Also es war von der Benutzung her, ähm, also wenn es um die Mahlzeiten ging. Ich finde war das ungefähr das gleiche.

Theme	Question	Deductive	Inductive	Example Sentence
FutureUsage	Tell us how you would like to continue using Nutrilize	Payment	CostFree	Kommt drauf an ja, ist die dann, kostet die dann was? ... Wahrscheinlich würde ich erst mal gucken, ob es kostenlose Apps irgendwo gibt.
		DurationAndFrequency	NotAlways	Aber ich glaube auch, dass es auch begrenzt ist, das kann man auch nicht die ganze Zeit nutzen.
			LessFrequent	Also, muss mal gucken, ob ich da noch die Zeit, also hab. Ich hab am Ende jetzt gedacht, das war ziemlich zeitaufwändig schon immer. War, dass man immer beim Essen mit dem Handy dasitzt und so.
			WouldLikeTo	Ja das würde ich sehr gerne weiter, hm weiterhin, weiterhin die Einträge machen. Ähm und schauen, wie sich das entwickelt, mit meinem Gewicht. ... Und ähm, den anderen Indikatoren. ...
			OnlyIfImproved	Ja also, sagen wir mal natürlich klar, das ist ein Entwicklungsprojekt, da funktioniert einfach nicht alles so wie es soll. Aber im Echtbetrieb würde ich die App in der Form so natürlich nicht einsetzen.
			NotUse	Und das fühlt sich auch an als befreiend. Dass man nicht mehr alles nach, also als Recht werten muss. Dass es hat da eine Zeit lang wirklich gute Anregungen gegeben, aber ich möchte ja auch nicht zum gestörten Kalorienzähler werden.
		Improvement	MoreContent	Was mir leider nicht so gut gefallen hat. Dass ich nicht alles finden konnte, was ich, ähm, was ich gegessen habe.
			TooSlow	Mh, also ich find? sie lädt immer ziemlich lange. ... So auch wenn, wenn auch dieses Essenstagebuch und so, das braucht immer. Und immer, wenn man wieder zurückgeht, also das lädt immer wieder neu diese Seite. Also, ja das vielleicht. Das würde ich bisschen ändern.
			TooLittlePressure	Also ich brauche immer ein bisschen Druck, dass ich dann eine halbe Stunde Sport mache, oder so was. Ich kenne mich, so ein Druck halt. Das war ja hier gar nicht, war ja alles okay, was man da so einträgt. Es kam ja nie eine Wertung.
			OwnRecipes	Ähm es ist wie gesagt, vielleicht da ein bisschen verbesserungsfähig. ... Also zum Beispiel eigene Rezepte einzufügen. ... Ja und so Kantinenessen und Fertigprodukte, das war alles aufgeführt auch in der App. Das ist alles Essen, was wir ja gar nicht zu uns nehmen.
			BarcodeScanning	Oder eben über verpackte Lebensmittel, dass man über, auch über den Barcode eingeben könnte.
			BetterRecommendations	Da fand ich immer so, dass die Empfehlungen nicht unbedingt zu mir gepasst haben, oder das auch nicht so das Essen war, wo ich sage, oh da hätte ich jetzt so wahnsinnige Lust drauf, dann esse ich lieber das, statt irgendwas anderes, was mir jetzt halt so in den Sinn gekommen wäre.
			EasierTracking	Oder was auch saublöd war, dass man es am nächsten Tag erst gemacht hat, weil man es aus welchen Gründen auch immer nicht geschafft hat. Dann musst du ja immer wieder in dieses Menü rein gehen, das also, der Tag bleibt zwar der gleiche, aber da muss man immer wieder bei Frühstück und dann wieder das nächste Produkt da rein und dann erst wieder warten, bis sich das wieder lädt und dann wieder das nächste Produkt da rein. Also das fand ich wahnsinnig umständlich.
			Defaults	Aber es würde das ganze charmanter machen, wenn man auf einen Rutsch sagen kann, ich esse jeden Morgen dieses Müsli, also kann ich das so rüber ziehen. ... Und auch miit den Größenordnungen. Ni, wenn ich ungefähr immer die gleichen ess, dass es die einfach mit rüber nimmt, dass ich nicht eingeben muss, ich hab einen halben Apfel und eine halbe Banane genommen, dass es schon so voreingestellt ist. Ni, so Voreinstellungen machen könnte die man mit rüber ziehen kann.
			InformationOnMealLevel	Also was mich vielleicht noch mehr interessieren würde, wäre dann doch dass man so eine Übersicht bekommt, ähm Ihr Frühstück hatte heute gesamt, was weiß ich, 500 Kalorien, Ihr Mittagessen hatte heute gesamt 800 Kalorien. ... Und Ihr Abendessen hatte so und so viele Kalorien, dass man da so die einzelnen Mahlzeiten sehen könnte, wo das heute zum Beispiel gehapert hat Also wo man sagt Mensch, äh, hätte ich heute das Mittagessen so ein bisschen, ja ich sage mal fettärmer gestaltet, das wäre vielleicht auf die Parameter jetzt nicht so weit ausgeschlagen, oder wie auch immer. Also das wäre vielleicht glaube ich nochmal so ganz gut.
			TooMuchDetail	Also grade zum Beispiel bei den verschiedenen Käsen. ... Finde ich jetzt. Ob jetzt der dreifach fünf Prozent hat oder fünf Komma fünf, oder ähm, diese geringen Sprünge. Ähm das war mir ein bisschen zu detailliert. ... Mh, die Statistik. ... Ähm die ist ein bisschen zu, nach meiner Meinung zu aufwändig.
	Tell us how you would replace Nutzilize	OtherApp	OtherApp	Muss ich mal gucken, also die, ich glaub Balance hieß die von runtastic oder so was.
		OtherTracking	OtherTracking	Gib ein was du gegessen und getrunken hast, ähm, von daher, um dabei zu bleiben. ... Bei der Thematik wäre es sicher sinnvoll nach einer Alternative zu suchen, klar. ... Sonst reißt das wieder ein, dass man ein bisschen, ja sagen wir mal nachlässig wird. ...Ich schaue mal ob ich was finde, denn es hat da so ähm, sage mal Tagesablauf beeinflusst. Äh und hat mir am Abend immer wieder gesagt, so jetzt setzt du dich hin.
			SportsTracking	Ähm, das liegt auch daran, dass ich so einen portablen Fitnesstrecker benutze und die lassen sich ja synchronisieren.
		-	OtherMotivation	Aber der Sommer steht ja von der Türe und da äh, ist die Gefahr, dass man nachlässig wird nicht ganz so groß. Weil ja da die Jeans passen muss und der Bikini und man möchte ja in die Berge zum wandern gehen. Also da kriegt man genug Anregungen auch von außen.
		-	OtherInfos	Ähm, also ich werde sicherlich immer wieder mal auch was im Internet recherchieren.
		OtherFeedback	NutritionFeedback	Also ich hab es mir überlegt schon. Also einfach nur, weil?s mich interessiert, was man so an Nährstoffen isst. Also ich will jetzt nicht abnehmen, oder so, deshalb ja.
		-	NoApp	Das ist aber bei mir auch so, eigentlich versuche ich das generell zu vermeiden, auch so aus Datenschutzgründen. Weil ich Angst habe, dass es irgendwie mal ausgelesen wird.

Theme	Question	Deductive	Inductive	Example Sentence
Changes in Behaviour and Motives	Tell us how your perception of eating has changed	Pleasure	Pleasure	Ich esse gerne, ich koche jeden Tag.... Mache ich wirklich mit frischen Zutaten und ich bleibe auch dabei. Das ist der größte Luxus, den ich mir leisten kann und das ziehe ich so lange durch, so lange mir das möglich ist.
			NoConstraints	Also ich habe mich jetzt auch nicht eingeschränkt gefühlt, in dem Sinne, dass ich jetzt sage, das und das sollte ich jetzt nicht mehr essen, oder. Ähm, das hat mich jetzt, das System nicht besonders, äh, kasteit, dass ich jetzt sage, nein das isst du nicht mehr.
		SocialBehaviour	SocialBehaviour	Also mein Partner kocht auch viel. Dann wenn ich dann darauf hingewiesen habe, dass eher weniger Salz, oder weniger Fett zum braten benutzen soll. Aber direkt Konflikte gab es deswegen nicht.
		Planning	-	
		Consciousness	Weight	Und auch das ein, also, als ich dann daheim war, da hab ich mich dann wieder gewogen. Also das hab ich dann schon gemerkt, die vier Tage irgendwie. Schon bisschen krass. Also es wäre mir vorher wahrscheinlich gar nicht aufgefallen, wenn ich das nicht gemacht hätte mit der App.
			FoodItems	Na auf jeden Fall hat man mal bewusster gegessen. Und dann überlegt, also äh, ja wie gesagt, du hast halt heute das und das und das gegessen.
			Nutrients	Aber dass man halt dann praktisch, ähm, wenn ich mal beim einen etwas zu viel oder zu wenig hab, dass man halt das, oder dass ich das, muss immer von mir reden, ähm, dass ich das halt dann versuche die nächsten Tage dann irgendwie auszugleichen.
			Portions	Ich habe das ja beim letzten Gespräch schon gesagt, dass weniger ja, oder vielleicht das Gefühl auch vermittelt bekommen habe, dass ja weniger auch für mich ausreichend ist, oder eigentlich meinem Bedarf entspricht.
	Tell us how you will sustain your changes	Difficulties	Effort	Mh, also ich glaub, also, ich dachte immer wir, also mir ist es eigentlich immer zu anstrengend irgendwie so drauf zu achten, ähm, was ich esse, oder wie viel ich von was esse, was drin ist und so.
			Helplessness	Und dass man nie schafft alles in Einklang zu bringen. Das ist ein Ding der Unmöglichkeit praktisch.
			NoDifficulties	Überhaupt nicht. Gab keine Schwierigkeiten von meiner Seite her jetzt. Wie gesagt ich bin sehr diszipliniert.
		Relapse	SocialFactors	Also schwer fand ich es zum Beispiel immer, wenn wir bei meinen Eltern zu Besuch waren, weil da gibt es halt immer häufiger mal Kuchen und so weiter. Das ist dann irgendwie schon ein bisschen blöd auch sich da einzuschränken.
			Restaurant	Und was wahnsinnig schwer ist, ist wenn man essen geht. Also das ist ja faktisch unmöglich, sage ich jetzt mal da dann wirklich zu sagen, okay, äh, die halbe Portion würde ja eigentlich reichen.
			Events	Ähm, sicherlich durch Ostern bedingt, äh, da auch wieder irgendwie, sag ich mal die Süßigkeiten, oder die Schokolade im Vordergrund stand.
		LongTermChange	KnowledgeGain	Und ich glaube durch die App hab ich das jetzt also so ein bisschen automatisch drin, was, was gut ist und was nicht.
			Reduction	Ich habe ganz normal weiter gegessen tagsüber, aber dafür am Abend reduziert und ja. Ich habe ein bisschen weniger gegessen.
			NewHabits	Also in gewisser Hinsicht ja, dass ich vielleicht versuche hier und da mehr Vollkornprodukte zu essen, oder Vollkornmüsli, oder ähnliches
InteractionChanges	Tell us about changes in your interaction with Nutrilize	EaseOfUse	EaseOfUse	Aber im großen und Ganzen bin ich besser zurechtgekommen, als beim Anfang. ... Aber ich habe mich besser eingefunden in die App.
		LeaveOutSteps	LessFeedback	Also ich habe jetzt da nicht mehr so genau rein geschaut. Weil ich ja so im groben wirklich den Überblick habe, äh, was ich so esse.
			LessInput	Aber wenn ich jetzt ein anderes Essen eingeben möchte, mein Goulasch ohne Geschmacksverstärker, ohne Mehl, ohne Dinge, die vielleicht in einem Kantinenessen drin sind, ähm, dann weicht das natürlich ab
		OwnPatterns	NewContent	Ich habe mich noch mehr rein gelesen. Ich habe beim Sport das eine, oder andere Jetzt gefunden.
			Habit	Na eigentlich nicht mehr, weil hm, das war schon recht lange in Betrieb letztlich. Das hat sich schon eingespielt gehabt. Alles, ich habe alles so weiter gemacht wie bisher.

Theme	Question	Deductive	Inductive	Example Sentence
	Tell us about changes in your interaction with Nutrilize	Frequency	Timing	Ich habe es am Anfang immer so gemacht, dass eigentlich immer nach den Mahlzeiten das dann auch gleich äh, da dokumentiert habe und das ist mir irgendwie jetzt in der zweiten Hälfte ein bisschen schwieriger gefallen. Einfach aus den beruflichen Gründen. Und dann habe ich das immer erst abends gemacht.
		Duration	LessTime	Also weil, also (am Anfang) habe ich mir bisschen mehr Zeit genommen.
			MoreTime	Wahrscheinlich war auch ein bisschen mehr Zeit notwendig meinerseits, die ich auf aufgewendet habe dann.
		MotivesAndGoals	NewGoals	Ich habe mich eher auf den Sport konzentriert, weil ich ja walken gehe, ich gehe zum Radfahren, ich mache auch noch andere Dinge und da habe ich mehr Zeit, darauf jetzt verwendet, da einfach ein bisschen mehr zu ergänzen.
AppEffects	Tell us how your nutrition knowledge changed	FoodItems	NutrientsInFood	Ähm also, dass wenn man viel Leber isst, oder Paprika, habe ich festgestellt da geht das Vitamin A gleich brutal nach oben. Gleich über den guten Wert, gnadenlos.
			FoodItemsInDiet	Aber so, das Bewusstsein, ja jetzt könnte man noch einen Spinat dazu nehmen, oder den vielleicht weglassen, so was schon.
		-	NutrientRequirement	Also, ja man weiß jetzt was, welche Nährstoffe, die mir oft fehlen.
		Portions	CalorieRequirements	Ähm, dass mein Grundumsatz relativ niedrig ist. Dass ich auf jeden Fall weniger essen muss, als ich eigentlich denke ich könnte es essen.
			PortionSizeFoodItems	Aber also, ich hab gemerkt, dass man so ein bisschen das Gefühl dafür bekommt, wie viel man von was isst.
		PointsInTime	-	
	Tell us how you changed physically	Weight	LooseWeight	Ich hab auch 7 Kilo verloren.
			WatchWeight	Und auch das ein, also, als ich dann daheim war, da hab ich mich dann wieder gewogen. Also das hab ich dann schon gemerkt, die vier Tage irgendwie. Schon bisschen krass. Also es wäre mir vorher wahrscheinlich gar nicht aufgefallen, wenn ich das nicht gemacht hätte mit der App.
		Performance	MorePhysicalActivity	Das würde ich aber tatsächlich eher auf den Sport, als auf die veränderte Ernährung zurück führen. Aber auch dazu animiert einen die App ja, dass man dann statt 20 Minuten vielleicht dann doch 30 Minuten macht und dann kriegt man hinterher, kriegt man noch ein paar grüne Kalorien hinten drauf. Das unterstützt das ja auch.
			Tiredness	Habe ich festgestellt, dass wenn ich ein bisschen ausgeglichener ess?, dann bin ich nicht so müde.
		Wellbeing	Wellbeing	Aber das Wohlbefinden, was man schon merken muss an mir.
	Tell us how you changed mentally	ActionControl	AbilityToAct	Mh, also ich glaub, also, ich dachte immer wir, also mir ist es eigentlich immer zu anstrengend irgendwie so drauf zu achten, ähm, was ich esse, oder wie viel ich von was esse, was drin ist und so. Und ich glaube durch die App hab ich das jetzt also so ein bisschen automatisch drin, was, was gut ist und was nicht.
		Emotions	Annoyance	Also ich glaube, wenn man jetzt sagt, man muss jetzt wirklich irgendwie so ein halbes Jahr jeden Tag da dokumentieren, also da kommt schon irgendwann dann mal ein bisschen, ach ich möchte jetzt auch gar nicht Frustration sagen, aber irgendwie kommt Genervtheit dem System gegenüber glaube ich, dann mal auf.
			Satisfaction	Naja grade so an Tagen wo, wo dann am Ende der gelbe Balken dann nicht über den erlaubten Kalorien liegt und wenn dann auch so am nächsten Tag dann so gezeigt hat, jetzt ist da statt 19 plötzlich 21 werte im Optimum. Das macht zufrieden. ...Da ist man dann mit sich zufrieden.
		Joy	GoodMood	Oder einfach so generell von der Stimmung her, aber ich fühle mich auf jeden Fall gut.
		-	UnchangedOrDueToExternalReasons	Ähm, weiß ich nicht, ob ich mich besser fühle. Also ich würde mal eher sagen es ist gleich geblieben. ... Es ist in meinem Leben so viel los, dass ich da gar nicht sagen kann, warum äh, ich manchmal so angespannt bin, oder eben nicht.

Part VI

BIBLIOGRAPHY

BIBLIOGRAPHY

Abt, C. C. (1987). *Serious games*. University press of America.

Ajzen, I. (2002). Constructing a tpb questionnaire: Conceptual and methodological considerations.

Ajzen, I. et al. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, 50(2):179–211.

Akaike, H. (1974). A new look at the statistical model identification. *IEEE transactions on automatic control*, 19(6):716–723.

Allen, J. K., Stephens, J., Dennison Himmelfarb, C. R., Stewart, K. J., and Hauck, S. (2013). Randomized controlled pilot study testing use of smartphone technology for obesity treatment. *Journal of obesity*, 2013.

Amresh, A., Lyles, A., Small, L., and Gary, K. (2017). Fitbit garden: A mobile game designed to increase physical activity in children. In *Proceedings of the 2017 International Conference on Digital Health*, pages 200–201. ACM.

Anderson, D. M. (2002). Hungry red planet: Children's multimedia nutrition simulation software. In *The 130th Annual Meeting of APHA*.

Arbeitsgemeinschaft Adipositas im Kindes- und Jugendalter (2011). My bmi 4 kids. https://aga.adipositas-gesellschaft.de/mybmi4kids/. Accessed: 2020-05-01.

Azar, K. M., Lesser, L. I., Laing, B. Y., Stephens, J., Aurora, M. S., Burke, L. E., and Palaniappan, L. P. (2013). Mobile applications for weight management: theory-based content analysis. *American journal of preventive medicine*, 45(5):583–589.

Baecke, J. A., Burema, J., and Frijters, J. E. (1982). A short questionnaire for the measurement of habitual physical activity in epidemiological studies. *The American journal of clinical nutrition*, 36(5):936–942.

Bao, L. (2018). Qualitative reasearch concept focusgroup: Fit food fun. Bachelor's thesis, Technical University of Munich.

Baranowski, T., Baranowski, J., Thompson, D., Buday, R., Jago, R., Griffith, M. J., Islam, N., Nguyen, N., and Watson, K. B. (2011). Video game play, child diet, and physical activity behavior change: A randomized clinical trial. *American journal of preventive medicine*, 40(1):33–38.

Baranowski, T., Buday, R., Thompson, D., Lyons, E. J., Lu, A. S., and Baranowski, J. (2013). Developing games for health behavior change: Getting started. *GAMES FOR HEALTH: Research, Development, and Clinical Applications*, 2(4):183–190.

Baranowski, T., Buday, R., Thompson, D. I., and Baranowski, J. (2008a). Playing for Real. *American Journal of Preventive Medicine*, 34(1):74–82.e10, ISSN: 07493797.

Baranowski, T., Buday, R., Thompson, D. I., and Baranowski, J. (2008b). Playing for real: video games and stories for health-related behavior change. *American journal of preventive medicine*, 34(1):74–82.

Baranowski, T., Lyons, E. J., and Thompson, D. (2019a). Experimental design to systematically develop a knowledge base for effective games for health.

Baranowski, T., Ryan, C., Hoyos-Cespedes, A., and Lu, A. S. (2019b). Nutrition education and dietary behavior change games: A scoping review. *Games for health journal*, 8(3):153–176.

Barounig, T., Wandinger, M., and Rushing, S. (2017). Enable project - cooking app. Master games lab course, Technical University of Munich.

Baxter, G. and Sommerville, I. (2011). Socio-technical systems: From design methods to systems engineering. *Interacting with computers*, 23(1):4–17.

Beckert-Zieglschmid, C. and Brähler, E. (2007). *Der Leipziger Lebensstilfragebogen für Jugendliche (LLfJ): ein Instrument zur Arbeit mit Jugendlichen; das Handbuch; mit zahlreichen Tabellen*. Vandenhoeck & Ruprecht.

Berkovsky, S., Coombe, M., Freyne, J., and Bhandari, D. (2010). Isn't it great?: you can play, mate! In *Proceedings of the 15th international conference on Intelligent user interfaces*.

Bert, F., Giacometti, M., Gualano, M. R., and Siliquini, R. (2014). Smartphones and health promotion: A review of the evidence. *Journal of Medical Systems*, 38(1), ISBN: 1573-689X (Electronic)\r0148-5598 (Linking), ISSN: 01485598, DOI: 10.1007/s10916-013-9995-7.

Bielik, P., Tomlein, M., Krátky, P., Mitrík, Š., Barla, M., and Bieliková, M. (2012). Move2Play: An Innovative Approach to Encouraging People to Be More Physically Active. *Proceedings of the 2nd ACM SIGHIT symposium on International health informatics - IHI '12*, page 61, ISBN: 9781450307819.

Blakely, G., Skirton, H., Cooper, S., Allum, P., and Nelmes, P. (2009). Educational gaming in the health sciences: systematic review. *Journal of Advanced Nursing*, 65(2):259–269.

Böker, C. J. (2018). Integration and evaluation of an avatar in serious games for nutrition. Bachelor's thesis, Technical University of Munich.

Bond, T. G. and Fox, C. M. (2013). *Applying the Rasch model: Fundamental measurement in the human sciences*. Psychology Press.

Brooke, J. et al. (1996). Sus-a quick and dirty usability scale. *Usability evaluation in industry*, 189(194):4–7.

Brown, C. M. (1998). *Human-computer interface design guidelines*. Intellect Books, Exeter, ISBN: 1871516544.

Brown, S. J., Lieberman, D. A., Gemeny, B., Fan, Y. C., Wilson, D., and Pasta, D. (1997). Educational video game for juvenile diabetes: results of a controlled trial. *Medical informatics*, 22(1):77–89.

Calvo, R. A. and Peters, D. (2014). *Positive computing: technology for wellbeing and human potential*. MIT Press.

Carter, M. C., Burley, V. J., Nykjaer, C., and Cade, J. E. (2013). Adherence to a smartphone application for weight loss compared to website and paper diary: pilot randomized controlled trial. *Journal of medical Internet research*, 15(4):e32.

Carver, C. S. and Scheier, M. F. (1982). Control theory: A useful conceptual framework for personality–social, clinical, and health psychology. *Psychological bulletin*, 92(1):111.

Celis-Morales, C., Livingstone, K., and Marsaux et al., C. (2016). Effect of personalized nutrition on health-related behaviour change: evidence from the food4me european randomized controlled trial. *International journal of epidemiology*, 46(2):578–588.

Celis-Morales, C., Livingstone, K. M., Marsaux, C. F., Forster, H., O'Donovan, C. B., Woolhead, C., Macready, A. L., Fallaize, R., Navas-Carretero, S., San-Cristobal, R., et al. (2015). Design and baseline characteristics of the Food4Me study: a web-based randomised controlled trial of personalised nutrition in seven European countries. *Genes and Nutrition*, 10(1):265494, ISBN: 1555-8932 (Print)\r1555-8932 (Linking), ISSN: 18653499.

Chantal, J., Hercberg, S., Organization, W. H., et al. (2017). Development of a new front-of-pack nutrition label in france: the five-colour nutri-score. *Public Health Panorama*, 3(04):712–725.

Chen, B., Vansteenkiste, M., Beyers, W., Boone, L., Deci, E. L., Van der Kaap-Deeder, J., Duriez, B., Lens, W., Matos, L., Mouratidis, A., Ryan, R. M., Sheldon, K. M., Soenens, B., Van Petegem, S., and Verstuyf, J. (2015a). Basic psychological need satisfaction, need frustration, and need strength across four cultures. *Motivation and Emotion*, 39(2):216–236, ISSN: 0146-7239.

Chen, J., Cade, J. E., and Allman-Farinelli, M. (2015b). The most popular smartphone apps for weight loss: a quality assessment. *JMIR mHealth and uHealth*, 3(4):e104.

Chen, M., Jia, X., Gorbonos, E., Hong, C. T., Yu, X., and Liu, Y. (2019). Eating healthier: Exploring nutrition information for healthier recipe recommendation. *Information Processing & Management*, page 102051.

Chen, Z.-H., Chien, T.-C., and Chan, T.-W. (2011). Using self-competition to enhance students' learning. In *International Conference on Technologies for E-Learning and Digital Entertainment*, pages 234–235. Springer.

Choi, L., Liu, Z., Matthews, C., and Buchowski, M. (2011). Validation of accelerometer wear and nonwear time classification algorithm. *Medicine and science in sports and exercise*, 43(2):357.

Chow, C. Y., Riantiningtyas, R. R., Kanstrup, M. B., Papavasileiou, M., Liem, D. G., and Olsen, A. (2019). Can games change children,Äôs eating behaviour? a review of gamification and serious games. *Food Quality and Preference*, page 103823.

Codecheck AG (2020). Codecheck. https://www.codecheck.info/. Accessed: 2020-05-01.

Consolvo, S., McDonald, D., Toscos, T., Chen, M., Froehlich, J., Harrison, B., Klasnja, P., LaMarca, A., LeGrand, L., Libby, R., , Smith, I., and Landay, J. (2008). Activity sensing in the wild: a field trial of ubifit garden. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 1797–1806. ACM.

Craigie, A., Lake, A., Kelly, S., Adamson, A., and Mathers, J. (2011). Tracking of obesity-related behaviours from childhood to adulthood: a systematic review. *Maturitas*, 70(3):266–284.

Creative Commons (2020). Cc by-sa 3.0. https://creativecommons.org/licenses/by-sa/3.0/. Accessed: 2020-04-01.

Cugelman, B. (2013). Gamification: what it is and why it matters to digital health behavior change developers. *JMIR Serious Games*, 1(1).

Dadaczynski, K., Schiemann, S., and Paulus, P. (2016). *Gesundheit spielend fördern: Potenziale und Herausforderungen von digitalen Spieleanwendungen für die Gesundheitsförderung und Prävention*. Beltz Juventa.

Davis, C., Bryan, J., Hodgson, J., and Murphy, K. (2015). Definition of the mediterranean diet; a literature review. *Nutrients*, 7(11):9139–9153.

Davis, M. C., Challenger, R., Jayewardene, D. N., and Clegg, C. W. (2014). Advancing socio-technical systems thinking: A call for bravery. *Applied ergonomics*, 45(2):171–180.

de Edelenyi, F. S., Egnell, M., Galan, P., Druesne-Pecollo, N., Hercberg, S., and Julia, C. (2019). Ability of the nutri-score front-of-pack nutrition label to discriminate the nutritional quality of foods in the german food market and consistency with nutritional recommendations. *Archives of Public Health*, 77(1):28.

Delgado-Noguera, M., Tort, S., Martínez-Zapata, M. J., and Bonfill, X. (2011). Primary school interventions to promote fruit and vegetable consumption: a systematic review and meta-analysis. *Preventive medicine*, 53(1-2):3–9.

DeSmet, A., Van Ryckeghem, D., Compernolle, S., Baranowski, T., Thompson, D., Crombez, G., Poels, K., Van Lippevelde, W., Bastiaensens, S., Van Cleemput, K., et al. (2014). A meta-analysis of serious digital games for healthy lifestyle promotion. *Preventive medicine*, 69:95–107.

Deterding, S., Dixon, D., Khaled, R., and Nacke, L. (2011). From game design elements to gamefulness: defining gamification. In *Proceedings of the 15th international academic MindTrek conference: Envisioning future media environments*.

DGE (2000). *Nutrition Report 2000*. Henrich Druck + Medien GmbH.

Dimitrov, D. and Rumrill Jr, P. (2003). Pretest-posttest designs and measurement of change. *Work*, 20(2):159–165.

Dishman, R., Hales, D., Sallis, J., Saunders, R., Dunn, A., Bedimo-Rung, A., and Ring, K. (2010). Validity of social-cognitive measures for physical activity in middle-school girls. *Journal of pediatric psychology*, 35(1):72–88.

Dombrowski, S. U., Sniehotta, F. F., Johnston, M., Broom, I., Kulkarni, U., Brown, J., Murray, L., and Araújo-Soares, V. (2012). Optimizing acceptability and feasibility of an evidence-based behavioral intervention for obese adults with obesity-related co-morbidities or additional risk factors for co-morbidities: An open-pilot intervention study in secondary care. *Patient Education and Counseling*, 87(1):108–119, ISBN: 0738-3991(Print), ISSN: 07383991.

Duckworth, A. L. and Seligman, M. E. (2006). Self-discipline gives girls the edge: Gender in self-discipline, grades, and achievement test scores. *Journal of educational psychology*, 98(1):198.

Dudley, D. A., Cotton, W. G., and Peralta, L. R. (2015). Teaching approaches and strategies that promote healthy eating in primary school children: a systematic review and meta-analysis. *International Journal of Behavioral Nutrition and Physical Activity*, 12(1):28.

Elsweiler, D., Frummet, A., and Harvey, M. (2020). Comparing wizard of oz & observational studies for conversational ir evaluation. *Datenbank-Spektrum*, pages 1–5.

Elsweiler, D. and Harvey, M. (2015). Towards automatic meal plan recommendations for balanced nutrition. In *Proc. of RecSys '15*, pages 313–316. ISBN: 978-1-4503-3692-5.

enable cluster (2020). Enable-cluster. https://www.enable-cluster.de/archiv/. Accessed: 2020-04-01.

Erdbrink, A., Kortmann, R., and Verbraeck, A. (2019). The context dependency of four persuasive game design principles. In *Neo-Simulation and Gaming Toward Active Learning*, pages 453–461. Springer.

Ernährungsumschau (2019). Personalisierte ernährungsempfehlungen direkt aufs smartphone. https://www.ernaehrungs-umschau.de/news/07-11-2017-personalisierte-ernaehrungsempfehlungen-direkt-aufs-smartphone/. Accessed: 2019-03-01.

EuroFIR (2020). Food composition databases. http://www.eurofir.org/food-information/food-composition-databases/. Accessed: 2020-04-01.

Evans, C. E., Christian, M. S., Cleghorn, C. L., Greenwood, D. C., and Cade, J. E. (2012). Systematic review and meta-analysis of school-based interventions to improve daily fruit and vegetable intake in children aged 5 to 12 y. *The American journal of clinical nutrition*, 96(4):889–901.

Evenson, K., Catellier, D., Gill, K., Ondrak, K., and McMurray, R. (2008). Calibration of two objective measures of physical activity for children. *Journal of sports sciences*, 26(14):1557–1565.

Fallaize, R., Franco, R. Z., Pasang, J., Hwang, F., and Lovegrove, J. A. (2019). Popular nutrition-related mobile apps: An agreement assessment against a uk reference method. *JMIR mHealth and uHealth*, 7(2):e9838.

Feierabend, S., Plankenhorn, T., and Rathgeb, T. (2016). *JIM Studie 2016, Jugend, Information, (Multi-) Media Basisstudie zum Medienumgang 12- bis 19-Jähriger in Deutschland*. Medienpädagogischer Forschungsverbund Südwest (mpfs).

Ferrara, G., Kim, J., Lin, S., Hua, J., and Seto, E. (2019). A focused review of smartphone diet-tracking apps: Usability, functionality, coherence with behavior change theory, and comparative validity of nutrient intake and energy estimates. *JMIR mHealth and uHealth*, 7(5):e9232.

Finglas, P. M., Berry, R., and Astley, S. (2014). Assessing and improving the quality of food composition databases for nutrition and health applications in europe: the contribution of eurofir. *Advances in Nutrition*, 5(5):608S–614S.

Fishbein, M. (1979). A theory of reasoned action: some applications and implications.

Flaherty, S.-J., McCarthy, M., Collins, A., and McAuliffe, F. (2018). Can existing mobile apps support healthier food purchasing behaviour? content analysis of nutrition content, behaviour change theory and user quality integration. *Public health nutrition*, 21(2):288–298.

Fogg, B. J. (2002). Persuasive technology: using computers to change what we think and do. *Ubiquity*, 2002(December):5.

Fogg, B. J. (2009). A behavior model for persuasive design. In *Proceedings of the 4th international Conference on Persuasive Technology*, page 40. ACM.

Food4Me Study (2016a). Effect of an internet-based, personalized nutrition randomized trial on dietary changes associated with the mediterranean diet: the food4me study. *The American journal of clinical nutrition*, 104(2):288–297.

Food4Me Study (2016b). Reproducibility of the Online Food4Me Food-Frequency Questionnaire for Estimating Dietary Intakes across Europe. *The Journal of Nutrition*, 146(5):1068–1075, ISSN: 0022-3166, DOI: 10.3945/jn.115.225078, https://doi.org/10.3945/jn.115.225078.

Forster, H., Walsh, M. C., Gibney, M. J., Brennan, L., and Gibney, E. R. (2015). Personalised nutrition: the role of new dietary assessment methods. *Proceedings of the Nutrition Society*, 75(1):96–105.

Forster, H., Walsh, M. C., O'Donovan, C. B., Woolhead, C., McGirr, C., Daly, E., O'Riordan, R., Celis-Morales, C., Fallaize, R., Macready, A. L., et al. (2016). A dietary feedback system for the delivery of consistent personalized dietary advice in the web-based multicenter food4me study. *Journal of medical Internet research*, 18(6):e150.

Franco, R. Z., Fallaize, R., Lovegrove, J. A., and Hwang, F. (2016). Popular nutrition-related mobile apps: a feature assessment. *JMIR mHealth and uHealth*, 4(3):e85.

Franz, M. J., VanWormer, J. J., Crain, A. L., Boucher, J. L., Histon, T., Caplan, W., Bowman, J. D., and Pronk, N. P. (2007). Weight-loss outcomes: a systematic review and meta-analysis of weight-loss clinical trials with a minimum 1-year follow-up. *Journal of the American Dietetic Association*, 107(10):1755–1767.

Freyne, J. and Berkovsky, S. (2010). Intelligent food planning. *Proceedings of the 15th international conference on Intelligent user interfaces - IUI '10*, page 321, ISBN: 9781605585154.

Friedman, N., Goldszmidt, M., and Wyner, A. (1999). Data analysis with bayesian networks: a bootstrap approach. In *Proceedings of the Fifteenth conference on Uncertainty in artificial intelligence*, pages 196–205.

Fritz, T., Huang, E. M., Murphy, G. C., and Zimmermann, T. (2014). Persuasive technology in the real world: a study of long-term use of activity sensing devices for fitness. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 487–496. ACM.

Fuchs, K. L., Haldimann, M., Vuckovac, D., and Ilic, A. (2018). Automation of data collection techniques for recording food intake: a review of publicly available and well-adopted diet apps. In *2018 International Conference on Information and Communication Technology Convergence (ICTC)*, pages 58–65. IEEE.

für Ernährung Österreichische Gesellschaft für Ernährung Schweizerische Gesellschaft für Ernährungsforschung Schweizerische Vereinigung für Ernährung), D.-A.-C. D. G. (2008). *Referenzwerte für die Nährstoffzufuhr*. Umschau Braus Verlag.

Ge, M., Ricci, F., and Massimo, D. (2015). Health-aware Food Recommender System. In *Proceedings of the 9th ACM Conference on Recommender Systems*.

Gibney, M., Vorster, H., and Kok, F. (2002). *Introduction to human nutrition*. Blackwell Science Oxford.

Glocker, M. L., Langleben, D. D., Ruparel, K., Loughead, J. W., Gur, R. C., and Sachser, N. (2009). Baby schema in infant faces induces cuteness perception and motivation for caretaking in adults. *Ethology*, 115(3):257–263.

Goldring, D. and Sharon, D. (2016). Low-cost spectrometry system for end-user food analysis. US Patent 9,377,396.

Gough, D., Kumosa, L., Routh, T., Lin, J., and Lucisano, J. (2010). Function of an implanted tissue glucose sensor for more than 1 year in animals. *Science Translational Medicine*.

Gregor, S. and Hevner, A. R. (2013). Positioning and presenting design science research for maximum impact. *MIS quarterly*, 37(2).

Greupner, T. (2015). Development of food-based dietary recommendations for personalized nutrition advice on the bases of the food4me study. Master's thesis, Technical University of Munich.

Groh, G. (2011). *Contextual Social Networking*. PhD thesis, Technische Universität München.

Guthrie, N., Bradlyn, A., Thompson, S., Yen, S., Haritatos, J., Dillon, F., and Cole, S. (2015). Development of an accelerometer-linked online intervention system to promote physical activity in adolescents. *PloS one*, 10(5):e0128639.

Gutmair, K. (2018). Automatisierte, personalisierte ernährungsempfehlungen mittels einer smartphone-applikation und deren einfluss auf das ernährungsverhalten sowie bestimmte gesundheitsparameter. Bachelor's thesis, Technical University of Munich.

Hammer, S., Seiderer, A., André, E., Rist, T., Kastrinaki, S., Hondrou, C., Raouzaiou, A., Karpouzis, K., and Kollias, S. (2015). Design of a lifestyle recommender system for the elderly: Requirement gatherings in germany and greece. In *PETRA '15*.

Hartmann, B., Bell, S., Vásquez-Caicedo, A., Götz, A., Erhardt, J., and Brombach, C. (2005). Der bundeslebensmittelschlüssel. *German Nutrient DataBase. Karlsruhe: Federal Research Centre for Nutrition and Food (BfEL)*.

Hartmann-Boyce, J., Johns, D., Jebb, S., Aveyard, P., and Group, B. W. M. R. (2014). Effect of behavioural techniques and delivery mode on effectiveness of weight management: systematic review, meta-analysis and meta-regression. *obesity reviews*, 15(7):598–609.

Harvey, M., Ludwig, B., and Elsweiler, D. (2013). You are what you eat: Learning user tastes for rating prediction. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 8214 LNCS:153–164.

Haussmann, S., Seneviratne, O., Chen, Y., Ne,Äôeman, Y., Codella, J., Chen, C.-H., McGuinness, D. L., and Zaki, M. J. (2019). Foodkg: A semantics-driven knowledge graph for food recommendation. In *International Semantic Web Conference*, pages 146–162. Springer.

Helander, E., Kaipainen, K., Korhonen, I., and Wansink, B. (2014). Factors related to sustained use of a free mobile app for dietary self-monitoring with photography and peer feedback: retrospective cohort study. *Journal of medical Internet research*, 16(4):e109.

Herlocker, J. L., Konstan, J. a., and Riedl, J. (2000). Explaining collaborative filtering recommendations. *Proceedings of the 2000 ACM conference on Computer supported cooperative work*, pages 241–250, ISBN: 1581132220, ISSN: 00318655.

Hermans, R. C., van den Broek, N., Nederkoorn, C., Otten, R., Ruiter, E. L., and Johnson-Glenberg, M. C. (2018). Feed the alien! the effects of a nutrition instruction game on children's nutritional knowledge and food intake. *Games for health journal*, 7(3):164–174.

Hermsen, S., Frost, J., Renes, R. J., and Kerkhof, P. (2016). Using feedback through digital technology to disrupt and change habitual behavior: A critical review of current literature. *Computers in Human Behavior*, 57:61–74.

Hevner, A. R. (2007). A three cycle view of design science research. *Scandinavian journal of information systems*, 19(2):4.

Hevner, A. R., March, S. T., Park, J., and Ram, S. (2004). Design Science in Information Systems Research. *MIS Quarterly*, 28(1):75–105, ISBN: 0276-7783, ISSN: 02767783.

Ho, M., Garnett, S. P., Baur, L. A., Burrows, T., Stewart, L., Neve, M., and Collins, C. (2013). Impact of dietary and exercise interventions on weight change and metabolic outcomes in obese children and adolescents: a systematic review and meta-analysis of randomized trials. *JAMA pediatrics*, 167(8):759–768.

Hochbaum, G., Rosenstock, I., and Kegels, S. (1952). Health belief model. *United States Public Health Service*.

Holzinger, A., Calero Valdez, A., and Ziefle, M. (2016). Towards interactive recommender systems with the doctor-in-the-loop. In *MUC '16*.

Holzmann, S., Pröll, K., Hauner, H., and Holzapfel, C. (2017). Nutrition apps: Quality and limitations. *An explorative investigation on the basis of selected apps. Ernaehrungs Umsch*, 64:80–89.

Horne, J., Madill, J., and Gilliland, J. (2017). Incorporating the ‚Äòtheory of planned behavior‚Äôinto personalized healthcare behavior change research: a call to action. *Personalized medicine*, 14(6):521–529.

Hors-Fraile, S., Rivera-Romero, O., Schneider, F., Fernandez-Luque, L., Luna-Perejon, F., Civit-Balcells, A., and de Vries, H. (2018). Analyzing recommender systems for health promotion using a multidisciplinary taxonomy: A scoping review. *International journal of medical informatics*, 114:143–155.

Howe, K. B., Suharlim, C., Ueda, P., Howe, D., Kawachi, I., and Rimm, E. B. (2016). Gotta catch‚Äôem all! pokémon go and physical activity among young adults: difference in differences study. *bmj*, 355:i6270.

Hu, J., Perer, A., and Wang, F. (2016). Data driven analytics for personalized healthcare. In *Healthcare Information Management Systems*. Springer.

Hu, Y., Koren, Y., and Volinsky, C. (2008). Collaborative filtering for implicit feedback datasets. In *2008 Eighth IEEE International Conference on Data Mining*, pages 263–272. Ieee.

Imoto, S., Kim, S. Y., Shimodaira, H., Aburatani, S., Tashiro, K., Kuhara, S., and Miyano, S. (2002). Bootstrap analysis of gene networks based on bayesian networks and nonparametric regression. *Genome Informatics*, 13:369–370.

Institute of Digital Media and Child Development Working Group on Games for Health, Baranowski, T., Blumberg, F., Buday, R., DeSmet, A., Fiellin, L. E., Green, C. S., Kato, P. M., Lu, A. S., Maloney, A. E., et al. (2016). Games for health for children,Äîcurrent status and needed research. *Games for health journal*, 5(1):1–12.

Jekauc, D., Voelkle, M., Wagner, M., Mewes, N., and Woll, A. (2013). Reliability, validity, and measurement invariance of the german version of the physical activity enjoyment scale. *Journal of Pediatric Psychology*, 38(1).

John, O. P., Donahue, E. M., and Kentle, R. L. (1991). The big five inventory-versions 4a and 54. In *Berkeley, CA: University of California, Berkeley, Institute of Personality and Social Research*.

Johns, D. J., Hartmann-Boyce, J., Jebb, S. A., Aveyard, P., and Group, B. W. M. R. (2014). Diet or exercise interventions vs combined behavioral weight management programs: a systematic review and meta-analysis of direct comparisons. *Journal of the Academy of Nutrition and Dietetics*, 114(10):1557–1568.

Johnsen, K., Ahn, S., Moore, J., Brown, S., Robertson, T., Marable, A., and Basu, A. (2014). Mixed reality virtual pets to reduce childhood obesity. *IEEE transactions on visualization and computer graphics*, 20(4):523–530.

Jungvogel, A., Wendt, I., Schäbethal, K., Leschik-Bonnet, E., and Oberritter, H. (2013). Überarbeitet: Die 10 regeln der dge. *Ernährungs Umschau*.

Kadomura, A., Li, C.-Y., Tsukada, K., Chu, H.-H., and Siio, I. (2014). Persuasive technology to improve eating behavior using a sensor-embedded fork. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*.

Kaipainen, K., Payne, C. R., and Wansink, B. (2012). Mindless eating challenge: retention, weight outcomes, and barriers for changes in a public web-based healthy eating and weight loss program. *Journal of medical Internet research*, 14(6):e168.

Kaiser, F. G., Byrka, K., and Hartig, T. (2010). Reviving campbell's paradigm for attitude research. *Personality and Social Psychology Review*, 14(4):351–367.

Kaiser, F. G. and Wilson, M. (2004). Goal-directed conservation behavior: The specific composition of a general performance. *Personality and individual differences*, 36(7):1531–1544.

Kammermeier, C. (2018). Evaluierung verschiedener aspekte eines schriftlichen kommunikationskonzepts im bereich ernährung und gesundheit. Bachelor's thesis, Technical University of Munich.

KANT, A. K. (1996). Indexes of overall diet quality: A review. *Journal of the American Dietetic Association*, 96(8):785 – 791, ISSN: 0002-8223.

Kapp, K. (2012). *The gamification of learning and instruction: game-based methods and strategies for training and education*. John Wiley & Sons.

Kaptein, M., De Ruyter, B., Markopoulos, P., and Aarts, E. (2012). Adaptive persuasive systems: a study of tailored persuasive text messages to reduce snacking. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 2(2):10.

Kaptein, M., Markopoulos, P., de Ruyter, B. E. R., and Aarts, E. H. L. (2009). Can you be persuaded? individual differences in susceptibility to persuasion. In *INTERACT*.

Kelders, S. M., Kok, R. N., Ossebaard, H. C., and Van Gemert-Pijnen, J. E. (2012). Persuasive system design does matter: a systematic review of adherence to web-based interventions. *Journal of medical Internet research*, 14(6):e152.

Keller, J. M. (2009). *Motivational design for learning and performance: The ARCS model approach*. Springer Science & Business Media.

Khan, A., Siddiqi, M., and Lee, S.-W. (2013). Exploratory data analysis of acceleration signals to select light-weight and accurate features for real-time activity recognition on smartphones. Technical report, Division of Information and Computer Engineering, Ajou University.

King, D., Greaves, F., Exeter, C., and Darzi, A. (2013). 'gamification': influencing health behaviours with games. *Journal of the Royal Society of Medicine*, 106 3:76–8.

Kirk, S., Penney, T., McHugh, T.-L., and Sharma, A. (2012). Effective weight management practice: a review of the lifestyle intervention evidence. *International journal of Obesity*, 36(2):178.

Kitzmann, K. M., Dalton III, W. T., Stanley, C. M., Beech, B. M., Reeves, T. P., Buscemi, J., Egli, C. J., Gamble, H. L., and Midgett, E. L. (2010). Lifestyle interventions for youth who are overweight: A meta-analytic review. *Health Psychology*, 29(1):91.

Kniestedt, I. and Gómez Maureira, M. (2016). Little fitness dragon: A gamified activity tracker. In *Entertainment Computing - ICEC 2016*, pages 205–210.

Knijnenburg, B. P. and Willemsen, M. C. (2015). Evaluating recommender systems with user experiments. In *Recommender Systems Handbook*, pages 309–352. Springer.

Knijnenburg, B. P., Willemsen, M. C., Gantner, Z., Soncu, H., and Newell, C. (2012). Explaining the user experience of recommender systems. *User Modeling and User-Adapted Interaction*, 22(4-5):441–504.

Koch-Wiki (2019). Koch-wiki. https://www.kochwiki.org/. Accessed: 2020-04-01.

Kohl, L. F., Crutzen, R., and de Vries, N. K. (2013). Online prevention aimed at lifestyle behaviors: a systematic review of reviews. *Journal of medical Internet research*, 15(7):e146.

Kohli, S. and Chadha, R. (2018). Promotion of healthy food choices and eating habits among school children using video games. *School Health & Wellbeing*.

Kurth, B.-M. (2006). Informationen für teilnehmer der kiggs-studie.

Kusmierczyk, T., Trattner, C., and Nørvåg, K. (2015). Temporality in online food recipe consumption and production. In *Proceedings of the 24th International Conference on World Wide Web*, pages 55–56.

Laing, B. Y., Mangione, C. M., Tseng, C.-H., Leng, M., Vaisberg, E., Mahida, M., Bholat, M., Glazier, E., Morisky, D. E., and Bell, D. S. (2014). Effectiveness of a smartphone application for weight loss compared with usual care in overweight primary care patients: a randomized, controlled trial. *Annals of internal medicine*, 161(10_Supplement):S5–S12.

Lathia, N. (2012). Using ratings to profile your health. In *RecSys '12*.

Lavelle, H., Mackay, D., and Pell, J. (2012). Systematic review and meta-analysis of school-based interventions to reduce body mass index. *Journal of Public Health*, 34(3):360–369.

Le, H. P. (2016). Design and implementation of a serious game focused around nutrition. Bachelor's thesis, Technical University of Munich.

Lee, E., Choi, J., Ahn, A., Oh, E., Kweon, H., and Cho, D. (2015). Acceptable macronutrient distribution ranges and hypertension. *Clinical and Experimental Hypertension*.

Lemstra, M., Bird, Y., Nwankwo, C., Rogers, M., and Moraros, J. (2016). Weight loss intervention adherence and factors promoting adherence: a meta-analysis. *Patient preference and adherence*, 10:1547.

Levesque, C. S., Williams, G. C., Elliot, D., Pickering, M. A., Bodenhamer, B., and Finley, P. J. (2006). Validating the theoretical structure of the treatment self-regulation questionnaire (tsrq) across three different health behaviors. *Health education research*, 22(5):691–702.

Lin, J., Mamykina, L., Lindtner, S., Delajoux, G., and Strub, H. (2006). Fish'n'steps: Encouraging physical activity with an interactive computer game. In *International conference on ubiquitous computing*, pages 261–278.

Livingstone, K. M., Celis-Morales, C., Lara, J., Woolhead, C., O'Donovan, C. B., Forster, H., Marsaux, C. F., Macready, A. L., Fallaize, R., Navas-Carretero, S., et al. (2016). Clustering of adherence to personalised dietary recommendations and changes in healthy eating index within the food4me study. *Public health nutrition*, 19(18):3296–3305.

LLC, G. (2016). Sensors overview. `https://developer.android.com/guide/topics/sensors/sensors_overview.html`. Accessed: 2018-07-10.

LLC, G. (2019a). Calorie counter - myfitnesspal. `https://play.google.com/store/apps/details?id=com.myfitnesspal.android`. Accessed: 2019-05-29.

LLC, G. (2019b). Calorie counter by fatsecret. `https://play.google.com/store/apps/details?id=com.fatsecret.android`. Accessed: 2019-05-29.

LLC, G. (2019c). Lose it! - calorie counter. https://play.google.com/store/apps/details?id=com.fitnow.loseit. Accessed: 2019-05-29.

LLC, G. (2019d). Noom: Health & weight. https://play.google.com/store/apps/details?id=com.wsl.noom. Accessed: 2019-05-29.

Locke, E. a. and Latham, G. P. (2002). Building a practically useful theory of goal setting and task motivation. A 35-year odyssey. *The American psychologist*, 57(9):705–717, ISBN: 1935-990X (Electronic); 0003-066X (Print), ISSN: 0003-066X.

Long, Y. and Aleven, V. (2017). Educational game and intelligent tutoring system: A classroom study and comparative design analysis. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 24(3):1–27.

López-Nores, M., Blanco-Fernández, Y., Pazos-Arias, J., and Gil-Solla, A. (2012). Property-based collaborative filtering for health-aware recommender systems. In *Expert Systems with Applications*.

Luo, G., Thomas, S., and Tang, C. (2012). Automatic home medical product recommendation. *J. of Medical Systems*.

Lustria, M., Noar, S., Cortese, J., Van Stee, S., Glueckauf, R., and Lee, J. (2013). A meta-analysis of web-delivered tailored health behavior change interventions. *J. of Health Communication*.

Lyzwinski, L. (2014). A systematic review and meta-analysis of mobile devices and weight loss with an intervention content analysis. *Journal of personalized medicine*, 4(3):311–385.

Mack, I., Reiband, N., Etges, C., Eichhorn, S., Schaeffeler, N., Zurstiege, G., Gawrilow, C., Weimer, K., Peeraully, R., Teufel, M., Blumenstock, G., Giel, K., Junne, F., and Zipfel, S. (2019). The kids obesity prevention program (KOP): A cluster randomized controlled trial to evaluate a serious game for the prevention and treatment of childhood obesity (preprint). *Journal of Medical Internet Research*, DOI: 10.2196/15725, https://doi.org/10.2196/15725.

MacKinnon, D. P. (2011). Integrating mediators and moderators in research design. *Research on social work practice*, 21(6):675–681.

Madden, T. J., Ellen, P. S., and Ajzen, I. (1992). A comparison of the theory of planned behavior and the theory of reasoned action. *Personality and social psychology Bulletin*, 18(1):3–9.

Margetts, B. M. and Nelson, M. (1997). *Design concepts in nutritional epidemiology*. OUP Oxford.

Markland, D. and Tobin, V. (2004). A modification of the behavioral regulation in exercise questionnaire to include an assessment of amotivation. *Journal of Sport and Exercise Psychology*, 26.

Marsaux, C. F., Celis-Morales, C., Fallaize, R., Macready, A. L., Kolossa, S., Woolhead, C., O'Donovan, C. B., Forster, H., Navas-Carretero, S., San-Cristobal, R., et al. (2015). Effects of a web-based personalized intervention on physical activity in european adults: a randomized controlled trial. *Journal of medical Internet research*, 17(10):e231.

Mateo, G. F., Granado-Font, E., Ferré-Grau, C., and Montaña-Carreras, X. (2015). Mobile phone apps to promote weight loss and increase physical activity: a systematic review and meta-analysis. *Journal of medical Internet research*, 17(11):e253.

Mathers, J. C. (2019). Paving the way to better population health through personalised nutrition. *EFSA Journal*, 17:e170713.

Matomo (2020). Matomo. https://matomo.org/. Accessed: 2020-04-01.

Mauch, C. E., Wycherley, T. P., Laws, R. A., Johnson, B. J., Bell, L. K., and Golley, R. K. (2018). Mobile apps to support healthy family food provision: Systematic assessment of popular, commercially available apps. *JMIR mHealth and uHealth*, 6(12):e11867.

McAuley, E., Duncan, T., and Tammen, V. V. (1989). Psychometric properties of the intrinsic motivation inventory in a competitive sport setting: A confirmatory factor analysis. *Research quarterly for exercise and sport*, 60(1):48–58.

McClellan, M., Karumur, R., Vogel, R., Petzel, S., Cragg, J., Chan, D., Jacko, J., Sainfort, F., and Geller, M. (2016). Designing an educational website to improve quality of supportive oncology care for women with ovarian cancer: An expert usability review and analysis. *Intl. J. of Human-Computer Interaction*.

McKnight, D. H., Choudhury, V., and Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information systems research*, 13(3):334–359.

Meister, S., Becker, S., and Simson, U. (2016). Digitale gesundheit - unterstützung der adipositastherapie durch digitale technologien? *Adipositas - Ursachen, Folgeerkrankungen, Therapie KW - Adipositas KW - multimodale Therapie KW - Gewichtsreduktion KW - Mobile Health SN - 1865-1739*, 10(1):38–42.

Meyers, A., Johnston, N., Rathod, V., Korattikara, A., Gorban, A., Silberman, N., Guadarrama, S., Papandreou, G., Huang, J., and Murphy, K. P. (2015). Im2calories: towards an automated mobile vision food diary. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 1233–1241.

Michael, D. R. and Chen, S. L. (2005). *Serious games: Games that educate, train, and inform*. Muska & Lipman/Premier-Trade.

Michie, S., Abraham, C., Whittington, C., McAteer, J., and Gupta, S. (2009). Effective techniques in healthy eating and physical activity interventions: a meta-regression. *Health Psychology*, 28(6):690.

Michie, S., Richardson, M., Johnston, M., Abraham, C., Francis, J., Hardeman, W., Eccles, M., Cane, J., and Wood, C. (2013). The behavior change technique taxonomy (v1) of 93 hierarchically clustered techniques: building an international consensus for the reporting of behavior change interventions. *Annals of behavioral medicine*, 46(1):81–95.

Michie, S., Van Stralen, M. M., and West, R. (2011). The behaviour change wheel: a new method for characterising and designing behaviour change interventions. *Implementation science*, 6(1):42.

Miller, W. C., Koceja, D., and Hamilton, E. (1997). A meta-analysis of the past 25 years of weight loss research using diet, exercise or diet plus exercise intervention. *International journal of obesity*, 21(10):941.

Min, W., Jiang, S., and Jain, R. C. (2019). Food recommendation: Framework, existing solutions and challenges. *IEEE Transactions on Multimedia*.

Mishra, S. M. (2015). Google fit api. *Wearable Android™: Android Wear & Google Fit App Development*, pages 213–243.

Mitschenko, S. (2017). Design and implementation of a serious game focused around nutrition. Bachelor's thesis, Technical University of Munich.

Montagnese, C., Santarpia, L., Buonifacio, M., Nardelli, A., Caldara, A. R., Silvestri, E., Contaldo, F., and Pasanisi, F. (2015). European food-based dietary guidelines: a comparison and update. *Nutrition*, 31(7-8):908–915.

Moyon, F., Sajwan, A., and Nyokabi, A. (2017). Modeling and Visualization of Mobile Application for Smart Devices to Foster Healthier Living Styles . Guided research, Technical University of Munich.

Mück, C. (2017). Motivator avatar: Supporting healthy nutrition. Bachelor's thesis, Technical University of Munich.

Müller, M., Harvey, M., Elsweiler, D., and Mika, S. (2012). Ingredient matching to determine the nutritional properties of internet-sourced recipes. In *2012 6th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops*.

Mumford, E. (2006). The story of socio-technical design: Reflections on its successes, failures and potential. *Information systems journal*, 16(4):317–342.

Nacke, L. E., Bateman, C., and Mandryk, R. L. (2014). Brainhex: A neurobiological gamer typology survey. *Entertainment computing*, 5(1):55–62.

Neumann, M. (2017). Development of a mobile serious game to encourage a healthier living style. Bachelor's thesis, Technical University of Munich.

Neve, M., Morgan, P. J., Jones, P., and Collins, C. (2010). Effectiveness of web-based interventions in achieving weight loss and weight loss maintenance in overweight and obese adults: a systematic review with meta-analysis. *Obesity reviews*, 11(4):306–321.

Nordström, K., Juth, N., Kjellström, S., Meijboom, F., Görman, U., and Project, F. (2013). Values at stake: autonomy, responsibility, and trustworthiness in relation to genetic testing and personalized nutrition advice. *Genes & nutrition*.

Norman, A., Bellocco, R., Bergström, A., and Wolk, A. (2001). Validity and reproducibility of self-reported total physical activity—differences by relative weight. *International journal of obesity*, 25(5):682.

Nurmi, J., Knittle, K., Ginchev, T., Khattak, F., Helf, C., Zwickl, P., Castellano-Tejedor, C., Lusilla-Palacios, P., Costa-Requena, J., Ravaja, N., et al. (2020). Engaging users in the behavior change process with digitalized motivational interviewing and gamification: Development and feasibility testing of the precious app. *JMIR mHealth and uHealth*, 8(1):e12884.

of Medicine (US) Subcommittee on Interpretation, I. and of Dietary Reference Intakes; Institute of Medicine (US) Standing Committee on the Scientific Evaluation of Dietary Reference Intakes, U. (2000). *DRI Dietary Reference Intakes: Applications in Dietary Assessment*. Washington (DC): National Academies Press (US).

Oinas-Kukkonen, H. and Harjumaa, M. (2009). Persuasive systems design: Key issues, process model, and system features. *Communications of the Association for Information Systems*, 24(1):485–500, ISBN: 15293181, ISSN: 15293181.

Olson, C. M. (2016). Behavioral Nutrition Interventions Using e- and m-Health Communication Technologies: A Narrative Review. *Annual Review of Nutrition*, 36(1):annurev–nutr–071715–050815, ISSN: 0199-9885.

Orji, F. A., Greer, J., and Vassileva, J. (2019). Exploring the effectiveness of socially-oriented persuasive strategies in education. In *International Conference on Persuasive Technology*, pages 297–309. Springer.

Orji, R., Mandryk, R. L., and Vassileva, J. (2017a). Improving the efficacy of games for change using personalization models. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 24(5):1–22.

Orji, R., Mandryk, R. L., Vassileva, J., and Gerling, K. M. (2013). Tailoring persuasive health games to gamer type. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*.

Orji, R. and Moffatt, K. (2016). Persuasive technology for health and wellness: State-of-the-art and emerging trends. *Health Informatics Journal*, 1:26.

Orji, R., Nacke, L. E., and Di Marco, C. (2017b). Towards personality-driven persuasive health games and gamified systems. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pages 1015–1027.

Orji, R., Vassileva, J., and Mandryk, R. L. (2014). Modeling the efficacy of persuasive strategies for different gamer types in serious games for health. *User Modeling and User-Adapted Interaction*, 24(5):453–498.

Otten, J., Hellwig, J., and Meyers et al., L. (2006). *Dietary reference intakes: the essential guide to nutrient requirements*. National Academies Press.

Oyibo, K. and Vassileva, J. (2019). Investigation of the moderating effect of culture on users,Äô susceptibility to persuasive features in fitness applications. *Information*, 10(11):344.

Pearl, J. (1985). Bayesian networks: A model of self-activated memory for evidential reasoning.

Pinder, C., Vermeulen, J., Cowan, B. R., and Beale, R. (2018). Digital behaviour change interventions to break and form habits. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 25(3):1–66.

Prochaska, J. and Velicer, W. (1997). The transtheoretical model of health behavior change. *American journal of health promotion*, 12(1):38–48.

Pu, P. and Chen, L. (2007). Trust-inspiring explanation interfaces for recommender systems. *Knowledge-Based Systems*, 20(6):542–556, ISBN: 09507051, ISSN: 09507051.

Radha, M., Willemsen, M. C., Boerhof, M., and IJsselsteijn, W. A. (2016). Lifestyle Recommendations for Hypertension through Rasch-based Feasibility Modeling. *Proceedings of the 2016 Conference on User Modeling Adaptation and Personalization - UMAP '16*, pages 239–247, ISBN: 9781450343688.

Rammstedt, B., Kemper, C., Klein, M. C., Beierlein, C., and Kovaleva, A. (2013). Eine kurze skala zur messung der fünf dimensionen der persönlichkeit: Big-five-inventory-10 (bfi-10). *Methoden, Daten, Analysen (mda)*, 7(2):233–249.

Rapp, A., Tirassa, M., and Tirabeni, L. (2019). Rethinking technologies for behavior change: A view from the inside of human change. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 26(4):1–30.

Rateni, G., Dario, P., and Cavallo, F. (2017). Smartphone-based food diagnostic technologies: A review. *Sensors*, 17(6):1453.

Ravi, N., Dandekar, N., Mysore, P., and Littman, M. (2005). Activity recognition from accelerometer data. Technical report, Rutgers University.

Reimer, U. and Maier, E. (2016). An application framework for personalised and adaptive behavioural change support systems. In *ICT4AWE*.

Richards, C., Thompson, C., and Graham, N. (2014). Beyond designing for motivation: the importance of context in gamification. In *Proceedings of the first ACM SIGCHI annual symposium on Computer-human interaction in play*, pages 217–226.

Ridgers, N. D., McNarry, M. A., and Mackintosh, K. A. (2016). Feasibility and effectiveness of using wearable activity trackers in youth: A systematic review. *JMIR mHealth and uHealth*, 4(4).

Roberts, B. W., Kuncel, N. R., Shiner, R., Caspi, A., and Goldberg, L. R. (2007). The power of personality: The comparative validity of personality traits, socioeconomic status, and cognitive ability for predicting important life outcomes. *Perspectives on Psychological science*, 2(4):313–345.

Rohde, A., Lorkowski, S., Dawczynski, C., and Brombach, C. (2017). Dietary mobile apps: Acceptance among young adults. a qualitative study. *Ernahrungs Umschau*, 64(2):36–43.

Rokicki, M., Herder, E., Kuśmierczyk, T., and Trattner, C. (2016). Plate and prejudice: Gender differences in online cooking. In *Proceedings of the 2016 conference on user modeling adaptation and personalization*, pages 207–215.

Rösler, R. (2017). Iss - serious game for healthy diet. Bachelor's thesis, Technical University of Munich.

Ross Middleton, K., Patidar, S., and Perri, M. (2012). The impact of extended care on the long-term maintenance of weight loss: a systematic review and meta-analysis. *Obesity reviews*, 13(6):509–517.

Russell Stuart, J. and Norvig, P. (2009). *Artificial intelligence: a modern approach*. Prentice Hall.

Ryan, R. M. and Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American psychologist*, 55(1):68.

Sadasivam, R., Cutrona, S., Kinney, R., Marlin, B., Mazor, K., Lemon, S., and TK, H. (2016). Collective-intelligence recommender systems: Advancing computer tailoring for health behavior change into the 21st century. *J. of Medical Internet Research*.

Sahoo, D., Hao, W., Ke, S., Xiongwei, W., Le, H., Achananuparp, P., Lim, E.-P., and Hoi, S. C. (2019). Foodai: Food image recognition via deep learning for smart food logging. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 2260–2268.

Said, A. and Bellogín, A. (2014). Comparative recommender system evaluation: benchmarking recommendation frameworks. In *Proceedings of the 8th ACM Conference on Recommender systems*, pages 129–136.

Schmidt-Kraepelin, M., Thiebes, S., Stepanovic, S., Mettler, T., and Sunyaev, A. (2019). Gamification in health behavior change support systems-a synthesis of unintended side effects. In *Proceedings of the 14th International Conference on Wirtschaftsinformatik*, pages 1032–1046.

Schoeppe, S., Alley, S., Van Lippevelde, W., Bray, N. A., Williams, S. L., Duncan, M. J., and Vandelanotte, C. (2016). Efficacy of interventions that use apps to improve diet, physical activity and sedentary behaviour: a systematic review. *International Journal of Behavioral Nutrition and Physical Activity*, 13(1):127.

Schrepp, M., Hinderks, A., and Thomaschewski, J. (2014). Applying the user experience questionnaire (ueq) in different evaluation scenarios. In *International Conference of Design, User Experience, and Usability*, pages 383–392. Springer.

Schwarz, G. et al. (1978). Estimating the dimension of a model. *The annals of statistics*, 6(2):461–464.

Scutari, M. (2009). Learning bayesian networks with the bnlearn r package. *arXiv preprint arXiv:0908.3817*.

Shannon, J., Kristal, A. R., Curry, S. J., and Beresford, S. (1997). Application of a behavioral approach to measuring dietary change: the fat-and fiber-related diet behavior questionnaire. *Cancer Epidemiology and Prevention Biomarkers*, 6(5):355–361.

Soyer, S. (2017). Design of a mobile social game. Bachelor's thesis, Technical University of Munich.

Spectral Engines Oy (2018). Foodscanner. https://www.spectralengines.com/products/nirone-scanner/foodscanner. Accessed: 2020-05-01.

Sprague, D. and Tory, M. (2012). Exploring how and why people use visualizations in casual contexts: Modeling user goals and regulated motivations. *Information Visualization*, 11(2):106–123.

Stachl, C., Au, Q., Schoedel, R., Buschek, D., Völkel, S., Schuwerk, T., Oldemeier, M., Ullmann, T., Hussmann, H., Bischl, B., et al. (2019). Behavioral patterns in smartphone usage predict big five personality traits.

Städeli, C. (2013). *Kompetenzorientiert unterrichten-das AVIVA-Modell: fünf Phasen guten Unterrichts*. Hep der Bildungsverlag.

Starke, A., Willemsen, M., and Snijders, C. (2017). Effective user interface designs to increase energy-efficient behavior in a rasch-based energy recommender system. In *Proceedings of the Eleventh ACM Conference on Recommender Systems*, RecSys '17, pages 65–73, New York, NY, USA. ACM, ISBN: 978-1-4503-4652-8.

Stoyanov, S. R., Hides, L., Kavanagh, D. J., Zelenko, O., Tjondronegoro, D., and Mani, M. (2015). Mobile app rating scale: a new tool for assessing the quality of health mobile apps. *JMIR mHealth and uHealth*, 3(1):e27.

Straßburg, A. (2010). Ernährungserhebungen - methoden und instrumente. *Ernährungs Umschau*.

Strobl, R., Müller, M., Thorand, B., Linkohr, B., Autenrieth, C. S., Peters, A., and Grill, E. (2014). Men benefit more from midlife leisure-time physical activity than women regarding the development of late-life disability,Äîresults of the kora-age study. *Preventive medicine*, 62:8–13.

Struzek, A. (2015). Serious game for health: Food adventure. Bachelor's thesis, Technical University of Munich.

Südddeutsche Zeitung GmbH (2019). Südddeutsche zeitung. https://www.sueddeutsche.de/. Accessed: 2019-03-01.

Sun, L., Zhan, D., and Li, N. (2011). Physical activity monitoring with mobile phones. *Lecture Notes in Computer Science*, 6719:104–111.

Swinburn, B. A., Sacks, G., Hall, K. D., McPherson, K., Finegood, D. T., Moodie, M. L., and Gortmaker, S. L. (2011). The global obesity pandemic: shaped by global drivers and local environments. *The Lancet*, 378(9793):804–814.

Tang, P., Ash, J., Bates, D., Overhage, J., and Sands, D. (2006). Personal health records: Definitions, benefits, and strategies for overcoming barriers to adoption. *J. Am. Med. Inform. Assoc.*

Tangney, J. P., BOONE, A. L., and BAUMEISTER, R. F. (2018). High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. In *Self-Regulation and Self-Control*, pages 181–220. Routledge.

Tausch, A. P. and Menold, N. (2015). Methodische aspekte der durchführung von fokusgruppen in der gesundheitsforschung: welche anforderungen ergeben sich aufgrund der besonderen zielgruppen und fragestellungen?

Thaler, R. and Sunstein, C. (2008). *Nudge: Improving Decisions About Health, Wealth, and Happiness.* Penguin.

Theodoridis, T., Solachidis, V., Dimitropoulos, K., Gymnopoulos, L., and Daras, P. (2019). A survey on ai nutrition recommender systems. In *Proceedings of the 12th ACM International Conference on PErvasive Technologies Related to Assistive Environments*, pages 540–546.

Thompson, D., Baranowski, T., Buday, R., Baranowski, J., Thompson, V., Jago, R., and Griffith, M. J. (2010). Serious video games for health: How behavioral science guided the development of a serious video game. *Simulation & gaming*, 41(4):587–606.

Thompson, F. E. and Subar, A. F. (2017). Dietary assessment methodology. In *Nutrition in the Prevention and Treatment of Disease*, pages 5–48. Elsevier.

Thorndike, A. N., Riis, J., Sonnenberg, L. M., and Levy, D. E. (2014). Traffic-light labels and choice architecture: promoting healthy food choices. *American journal of preventive medicine*, 46(2):143–149.

Tintarev, N. and Masthoff, J. (2012). Evaluating the effectiveness of explanations for recommender systems. *User Modeling and User-Adapted Interaction*, 22(4-5):399–439.

Toledo, R. Y., Alzahrani, A. A., and Martínez, L. (2019). A food recommender system considering nutritional information and user preferences. *IEEE Access*, 7:96695–96711.

Tong, X., Gromala, D., Shaw, C., and Jin, W. (2015). Encouraging physical activity with a game-based mobile application: Fitpet. In *Games Entertainment Media Conference (GEM), 2015 IEEE*, pages 1–2.

Trang Tran, T. N., Atas, M., Felfernig, A., and Stettinger, M. (2018). An overview of recommender systems in the healthy food domain. *Journal of Intelligent Information Systems*, 50(3):501–526, ISSN: 15737675.

Trattner, D. and Elsweiler, D. (2019). Food recommender systems: Important contributions, challenges and future research directions. In Berkovsky, S., Cantador, I., and Tikk, D., editors, *Collaborative Recommendations: Algorithms, Practical Challenges and Applications*. World Scientific Publishing.

Trost, S. (2007). State of the art reviews: Measurement of physical activity in children and adolescents. *American Journal of Lifestyle Medicine*, 1(4).

TUM WZW (2019). App zur personalisierten ernährung im test. https://www.wzw.tum.de/index.php?id=185&tx_ttnews%5Btt_news%5D=1914&cHash=9b7d137be8f14b2a98a615ee8e290b75. Accessed: 2019-03-01.

Turkay, S. and Kinzer, C. K. (2014). The effects of avatar-based customization on player identification. *International Journal of Gaming and Computer-Mediated Simulations (IJGCMS)*, 6(1):1–25.

Turner-McGrievy, G. M., Helander, E. E., Kaipainen, K., Perez-Macias, J. M., and Korhonen, I. (2015). The use of crowdsourcing for dietary self-monitoring: crowdsourced ratings of food pictures are comparable to ratings by trained observers. *Journal of the American Medical Informatics Association*, 22(e1):e112–e119.

Union, E. (2011). Verordnung (eu) nr. 1169/2011 des europäischen parlaments und des rates vom 25. oktober 2011 betreffend die information der verbraucher über lebensmittel und zur änderung der verordnungen (eg) nr. 1924/2006 und (eg) nr. 1925/2006 des europäischen parlaments und des rates und zur aufhebung der richtlinie 87/250/ewg der kommission, der richtlinie 90/496/ewg des rates, der richtlinie 1999/10/eg der kommission, der richtlinie 2000/13/eg des europäischen parlaments und des rates, der richtlinien 2002/67/eg und 2008/5/eg der kommission und der verordnung (eg) nr. 608/2004 der kommission. 2011. *Amtsblatt der Europäischen Union (2011b)*, pages 18–63.

van Rossum, C. T., Fransen, H. P., Verkaik-Kloosterman, J., Buurma-Rethans, E. J., and Ocke, M. C. (2011). Dutch national food consumption survey 2007-2010: Diet of children and adults aged 7 to 69 years.

Venkatesh, V. and Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision sciences*, 39(2):273–315.

Viggiano, A., Viggiano, E., Di Costanzo, A., Viggiano, A., Andreozzi, E., Romano, V., Rianna, I., Vicidomini, C., Gargano, G., Incarnato, L., et al. (2015). Kaledo, a board game for nutrition education of children and adolescents at school: cluster randomized controlled trial of healthy lifestyle promotion. *European journal of pediatrics*, 174(2):217–228.

Wagner, C. H. (1982). Simpson's paradox in real life. *The American Statistician*, 36(1):46–48.

Wahl, D. R., Villinger, K., Blumenschein, M., König, L. M., Ziesemer, K., Sproesser, G., Schupp, H. T., and Renner, B. (2020). Why we eat what we eat: Assessing dispositional and in-the-moment eating motives by using ecological momentary assessment. *JMIR mHealth and uHealth*, 8(1):e13191.

Warren, J., Ekelund, U., Besson, H., Mezzani, A., Geladas, N., and Vanhees, L. (2010). Assessment of physical activity - a review of methodologies with reference to epidemiological research: a report of the exercise physiology section of the european association of cardiovascular prevention and rehabilitation. *European Journal of Cardiovascular Prevention and Rehabilitation*, 17(2).

Watson, W. S. and Correa, I. D. O. (2015). Analyzing and correlating spectra, identifying samples and their ingredients, and displaying related personalized information. US Patent 9,212,996.

Wenger, M. S., Bell, J., McEvoy, P., Yamaguchi, C., and Shokrpour, A. (2014). Bloom: fostering healthy and peaceful pregnancies with personal analytics. In *CHI'14 Extended Abstracts on Human Factors in Computing Systems*, pages 245–250. ACM.

West, J. H., Hall, P. C., Arredondo, V., Berrett, B., Guerra, B., and Farrell, J. (2013). Health behavior theories in diet apps. *Journal of Consumer Health On the Internet*, 17(1):10–24.

West, V. L., Borland, D., and Hammond, W. E. (2014). Innovative information visualization of electronic health record data: a systematic review. *Journal of the American Medical Informatics Association*, pages 1–7, ISBN: 1067-5027, ISSN: 1067-5027.

Westenbrink, S., Jansen-van der Vliet, M., Castenmiller, J., Grit, C., and Verheijen, P. (2016). Nevo-online 2016: achtergrondinformatie. *Nederlands Voedingsstoffenbestand*.

WHO (2008). Health topics - noncommunicable diseases - obesity - data and statistics. http://www.euro.who.int/en/health-topics/noncommunicable-diseases/obesity/data-and-statistics. Accessed: 2020-04-01.

WHO (2010). Global recommendations on physical activity for health. https://www.who.int/dietphysicalactivity/factsheet_recommendations/en/. Accessed: 2020-04-01.

WHO (2014). Global status report on noncommunicable diseases 2014. https://www.who.int/nmh/publications/ncd-status-report-2014/en/. Accessed: 2020-04-01.

WHO (2017a). New global estimates of child and adolescent obesity released on World Obesity Day. https://www.who.int/end-childhood-obesity/news/new-estimate-child-adolescent-obesity/en/. Accessed: 2020-04-01.

WHO (2017b). Noncommunicable Diseases Progress Monitor 2017. https://www.who.int/nmh/publications/ncd-progress-monitor-2017/en/. Accessed: 2020-04-01.

Wiafe, I. and Nakata, K. (2012). Bibliographic analysis of persuasive systems: Techniques; methods and domains of application. In *Persuasive Technology: Design for Health and Safety; The 7th International Conference on Persuasive Technology; Sweden; June 6-8; Adjunct Proceedings*.

Widmer, R. J., Collins, N. M., Collins, C. S., West, C. P., Lerman, L. O., and Lerman, A. (2015). Digital health interventions for the prevention of cardiovascular disease: a systematic review and meta-analysis. In *Mayo Clinic Proceedings*, volume 90, pages 469–480. Elsevier.

Wieland, L. S., Falzon, L., Sciamanna, C. N., Trudeau, K. J., Folse, S. B., Schwartz, J. E., and Davidson, K. W. (2012). Interactive computer-based interventions for weight loss or weight maintenance in overweight or obese people. *Cochrane Database of Systematic Reviews*, (8).

Wiesner, M. and Pfeifer, D. (2010). Adapting recommender systems to the requirements of personal health record systems. In *IHI '10*.

Wiesner, M. and Pfeifer, D. (2014). Health recommender systems: Concepts, requirements, technical basics and challenges. *IJERPH*.

Wilcox, L., Morris, D., Tan, D., and Gatewood, J. (2010). Designing patient-centric information displays for hospitals. In *CHI '10*.

Wilfley, D. E., Tibbs, T. L., Van Buren, D., Reach, K. P., Walker, M. S., and Epstein, L. H. (2007). Lifestyle interventions in the treatment of childhood overweight: a meta-analytic review of randomized controlled trials. *Health Psychology*, 26(5):521.

Williams, G. C., McGregor, H. A., Zeldman, A., Freedman, Z. R., and Deci, E. L. (2004). Testing a self-determination theory process model for promoting glycemic control through diabetes self-management. *Health Psychology*, 23(1):58.

Winsteps (2020). Winsteps and facets rasch software. https://www.winsteps.com/index.htm. Accessed: 2020-04-01.

Wong, W. L., Shen, C., Nocera, L., Carriazo, E., Tang, F., Bugga, S., Narayanan, H., Wang, H., and Ritterfeld, U. (2007). Serious video game effectiveness. In *Proceedings of the international conference on Advances in computer entertainment technology*.

Wu, T., Gao, X., Chen, M., and Van Dam, R. (2009). Long-term effectiveness of diet-plus-exercise interventions vs. diet-only interventions for weight loss: a meta-analysis. *Obesity reviews*, 10(3):313–323.

Yaramakala, S. and Margaritis, D. (2005). Speculative markov blanket discovery for optimal feature selection. In *Fifth IEEE International Conference on Data Mining (ICDM'05)*, pages 4–pp. IEEE.

Zeevi, D., Korem, T., Zmora, N., Israeli, D., Rothschild, D., Weinberger, A., Ben-Yacov, O., Lador, D., Avnit-Sagi, T., Lotan-Pompan, M., Suez, J., Mahdi, J., Matot, E., Malka, G., Kosower, N., Rein, M., Zilberman-Schapira, G., Dohnalová, L., Pevsner-Fischer, M., Bikovsky, R., Halpern, Z., Elinav, E., and Segal, E. (2015). Personalized Nutrition by Prediction of Glycemic Responses. *Cell*, 163(5):1079–1094, ISSN: 00928674.

Zhang, L., Nawijn, E., Boshuizen, H., and Ocké, M. (2019). Evaluation of the recipe function in popular dietary smartphone applications, with emphasize on features relevant for nutrition assessment in large-scale studies. *Nutrients*, 11(1):200.

Zhang, Z., Yang, Y., Yue, Y., Fernstrom, J., Jia, W., and Sun, M. (2011). Food volume estimation from a single image using virtual reality technology. In *Bioengineering Conference (NEBEC), 2011 IEEE 37th Annual Northeast*.

Ziegltrum, J. (2017). Development of a serious game to support a healthy diet. Master's thesis, Technical University of Munich.

SUPERVISED THESES

Appelhagen, J. (2015). Sports- and Activity-Recommender-Systems for Overweight Adolescents. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Bause, K. (2016). Design Concepts for improving Motivational Effects in an Avatar Based Educational Games Platform. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Borchers, A. (2018). Evaluation and Analysis of the Usability of a Serious Game about Nutrition. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Brandl, A. (2017). Design and Evaluation of Educational Elements in a Serious Game on Nutrition. Master's thesis, Technical University of Munich, advised by Hanna Schäfer.

Brunenberg, P. (2017). Knowledge Discovery in textual Databases for enhancing the automatic Calculation of nutritional Values for online-based Food recipes. Master's thesis, Technical University of Munich, advised by Hanna Schäfer.

Budiak, M. (2017). Automated Classification and Tagging of Online Recipes. Master's thesis, Technical University of Munich, advised by Hanna Schäfer.

Chau Lu, M. (2015). Socio-Technical Support for Group Motivation Processes. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Di Mango, S. (2018). Evaluation of a Serious Game on Healthy Nutrition regarding Motivation and Knowledge Gain. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Drost, F. (2018). Intelligent Retrieval of Nutritional Data for Supermarket Products. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Dubińska, M. (2018). Evaluation of Healthy Eating Recommendations regarding Novelty and Diversity over Time. Master's thesis, Technical University of Munich, advised by Hanna Schäfer.

Ezzeldin, M. (2016). Motivation for Healthy Living by User to User Feedback. Master's thesis, Technical University of Munich, advised by Hanna Schäfer.

Foegelle, L. (2016). Knowledge-based Recommendation Systems for Fitness. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Frenzel, L. (2017). Design and Evaluation of a User Interface for Recipe Recommendations in a Mobile Application. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Greger, A. (2016). Improvement of Recommender Systems through User Feedback. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Hecktor, R. (2015). Personalized Food Recommender Systems. Master's thesis, Technical University of Munich, advised by Hanna Schäfer.

Huang, S. (2016). Social Motivation for Healthy Living by Individual and Shared Game Concepts. Master's thesis, Technical University of Munich, advised by Hanna Schäfer.

Kienmoser, L. (2017). Integration von Verhaltensänderungsmodellen in Ernährungsempfehlungssystemen. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Ladek, T. (2017). User Motivation using Nudging and Explanations. Master's thesis, Technical University of Munich, advised by Hanna Schäfer.

Le, K. (2016). Social Motivation for Healthy Living by an Avatar Based Educational Games Platform. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Liu, D. (2016). Nutritional Information and Documentation through Mobile Systems. Interdisciplinary project, Technical University of Munich.

Loher, A. (2017). Motivation within a Serious Games Platform Using Social Network Elements. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Mainz, C. (2017). Interactive Visualization of Phases in Behaviour Change Models. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Mayer, M. (2017). Evaluation of Motivational Processes using a Social Nutrition Game. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Mohl, M. (2018). Machine Learning of Motivational and Behavior Change Stages from Nutritional Diaries. Master's thesis, Technical University of Munich, advised by Hanna Schäfer.

Müller, T. (2016). Effects of Social Motivation by Individual and Shared Challenges Related to Healthy Living. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Noglik, B. (2015). Games-Concepts Supporting Adolescents' Health via Exercising. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Otter, D. (2016). Designing a Group Recommender System for Healthy Nutrition. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Palm, J. (2017). Methods for Refactoring and Optimizing large Legacy Software Systems. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Petrov, I. (2016). Implementation and Evaluation of an Engaging Mobile Interaction Design for a Dietary Intake Tracking Application. Master's thesis, Technical University of Munich, advised by Hanna Schäfer.

Polácek, T. (2017). Evaluation of Motivational Elements in a Social Platform for Nutrition. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Prams, A. (2016). Evaluation of Different Concepts for the Automated Retrieval of Food Serving Sizes. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Pretscher, S. (2016). Tracking and Recognition of Movement Activity Using a Smartphone. Master's thesis, Technical University of Munich, advised by Hanna Schäfer.

Ramirez, L. (2017). Implementation of User Preference Models from Food Diaries. Master's thesis, Technical University of Munich, advised by Hanna Schäfer.

Sailer, M. (2017a). Group Motivation and Interaction Patterns for Social Games. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Sailer, M. (2017b). Study Methodology for Social Aspects in Serious Games. Guided research, Technical University of Munich, advised by Hanna Schäfer.

Schneider, R. (2015). Pragmatic Content Based Food Recommender Systems for Depressive Overweight Adolescents. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Schnelzer, C. (2016). Sequences and Diversity in Nutrition Recommender Systems. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Schober, F. (2016). Evaluation and Implementation of Computer Vision Concepts for Image Recognition of Food Items Using Deep Learning and SVMs. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Specht, B. (2016). Automated Retrieval of Nutritional Information for Different Food Databases. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Varady, C. (2018). Uncertainty Modelling for Healthy Nutrition Models. Master's thesis, Technical University of Munich, advised by Hanna Schäfer.

Wagner, G. (2016). Evaluation and Implementation of Usability Features for a Nutrition Recommender System. Master's thesis, Technical University of Munich, advised by Hanna Schäfer.

Walther, M. (2016). Socio-Technical Support of Group Creation and Group Management. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Weber, K. (2018). Design and Evaluation of a Serious Game concerning Increase of Knowledge and Motivation. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Weiher, T. (2018). Design and Evaluation of Building Blocks for a Serious Nutrition Games Platform. Master's thesis, Technical University of Munich, advised by Hanna Schäfer.

Wieser, F. (2018). Analysis of Interaction Patterns in Healthy Eating Applications. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Woerner, A. (2016). Development of a Serious Games Platform with a Central Avatar Concept. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.

Zuo, F. (2016). Evaluation of Motivation Concepts to Improve Active Participation in Fitness Game. Bachelor's thesis, Technical University of Munich, advised by Hanna Schäfer.