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Essays on the Role of Gamified Smartphone Applications for Physical Activity

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Summary (English)

Gamification, that is, the practice of using elements of game design in other areas than gaming, has been prominently incorporated in various contexts to enhance consumers' insights into their own health status and hence, motivate future physical activity and health behaviors. This dissertation presents three studies that provide an understanding of the role of gamified smartphone health and fitness applications (apps) for consumers' physical activity behaviors. Study 1 extends the Unified Theory of Acceptance and Use of Technology 2 in the context of smartphone health and fitness apps for physical activity and considers the moderating role of gamification-related app features. Using a sample of U.S. residents, the study assesses the downstream relationships on app usage intentions and behavioral intentions of being physically active. Study 2 reveals that the meaningful combination of gamification elements within smartphone health and fitness apps helped U.S. residents maintain physical activity during the emergence of Covid-19 (March 2020), by using a two-wave longitudinal design. Study 3 is the first systematic review with meta-analysis that synthesizes the implementations and pooled effects of standalone (i.e., without additional support and hence comparable to consumers' free-living usage) gamified health and fitness apps on physical activity among various users. Beside the identification of positive effects of app usage, the study reveals important gamification elements such as in-game rewards and leaderboards. Overall, this dissertation provides and quantitatively synthesizes evidence on the role of gamification implementations in smartphone health and fitness apps for consumers' physical activity. The dissertation contributes to the theories of gamification in mobile technology acceptance and consumer behavior, and gives an outlook on future

research such as investigating the isolated role of specific single or groups of gamification features in consumer behavior research.

Summary (German)

Gamification, auch bekannt als die Praxis der Verwendung von Elementen des Spieldesigns in anderen Bereichen als dem des Spielens, wurde prominent in verschiedenen Kontexten eingesetzt, um das Wissen der Verbraucher über ihren eigenen Gesundheitszustand zu verbessern und sie so zu künftigen körperlichen Aktivitäten und gesünderem Verhalten zu motivieren. Diese Dissertation präsentiert drei Studien, die die Rolle von spielerischen Gesundheits- und Fitnessanwendungen (Apps) auf dem Smartphone für das körperliche Aktivitätsverhalten der Verbraucher untersuchen. Studie 1 erweitert die Unified Theory of Acceptance and Use of Technology 2 im Kontext von Smartphone-Gesundheits- und Fitness-Apps für körperliche Aktivität und berücksichtigt die moderierende Rolle von gamifizierten App-Funktionen. Anhand einer Stichprobe von US-Bürgerinnen und -Bürgern werden Zusammenhänge zwischen der Absicht, eine App zu nutzen, und der Absicht, sich körperlich zu betätigen, untersucht. Studie 2 zeigt, dass die sinnvolle Kombination von Gamification-Elementen innerhalb von Smartphone-Gesundheits- und Fitness-Apps US-Bürgerinnen und -Bürgern geholfen hat, während des Auftretens von Covid-19 (März 2020) körperlich aktiv zu bleiben. Studie 3 ist die erste systematischer Review mit Meta-Analyse, der die Umsetzung und die zusammengefassten Effekte von eigenständigen (d.h. ohne zusätzliche Unterstützung und vergleichbar mit der Nutzung im Alltag der Verbraucher) gamifizierten Gesundheits- und Fitness-Apps auf die körperliche Aktivität bei verschiedenen Nutzern zusammenfasst. Neben der Beobachtung positiver Effekte der App-Nutzung werden wichtige Gamification-Elemente wie In-Game-Belohnungen und Bestenlisten identifiziert. Insgesamt liefert

diese Dissertation evidenzbasierte und quantitativ synthetisierte Erkenntnisse über die Rolle von Gamification-Implementierungen in Smartphone-Gesundheits- und Fitness-Apps für die körperliche Aktivität von Konsumentinnen und Konsumenten. Die Dissertation trägt zu den Theorien der Gamification in der Akzeptanz mobiler Technologien und des Konsumentenverhaltens bei und gibt einen Ausblick auf zukünftige Forschungsvorhaben, wie beispielsweise die Untersuchung der isolierten Rolle bestimmter einzelner oder gruppierter Gamification-Funktionen in der Konsumentenverhaltensforschung.

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List of Abbreviations

COVID-19: Coronavirus Disease 2019

eHealth: Electronic Health

GRADE: Grading of Recommendations Assessment, Development and Evaluation

IPAQ-SF: International Physical Activity Questionnaire Short Form

MET: Metabolic Equivalent of Task

mHealth: Mobile Health

PA: Physical Activity

PICOS: Population, Intervention, Comparison, Outcomes, and Study

PRISMA: Preferred Reporting Items for Systematic Reviews and Meta- Analyses guidelines

RCT: Randomized Controlled Trials

SMD: Standardized Mean Difference

TAM: Technology Acceptance Model

UTAUT2: The Unified Theory of Acceptance and Use of Technology 2

1. Introduction

Nudging consumers toward a healthier lifestyle is difficult (Mertens et al., 2022). Along with others such as smoking, diet, and alcohol consumption, physical activity is one of the most crucial lifestyle-related health behaviors, and insufficient physical activity has caused a substantial societal and economic burden (Ding et al., 2016). While there are various approaches to increase physical activity (e.g., implementations of social support and physical built-environments, and digital technologies), a framework of effective and feasible policy actions at the whole-of-society level (involving multiple stakeholders including governments, industry, and academia) is urgently needed (World Health Organization, 2019). Among these, digital health (also known as electronic health [eHealth]) products designed for consumers may help deliver cost-effective and evidence-based health promotion and care (World Health Organization, 2021), and have been widely developed to nudge individuals' behaviors to become more physically active. As the core part of digital health, mobile health tools (mHealth) such as consumer-based wearable trackers and smartphone applications (apps) have been proven particularly promising for consumers' health behaviors (Sim, 2019).

To further enhance the effectiveness of these mHealth products, gamification (e.g., using game design elements such as badges and points) has been used as a design strategy to increase users' immersion and joyfulness (Hamari, 2019). Yet, there are several research gaps in the current literature, particularly from the perspective of consumer behavior research, where the key challenge is to understand the consumers' (or users') decision-making process of acceptance, adoption, and effectiveness of mHealth products for physical activity. This dissertation focuses on the role of gamification in one of the primary mHealth products (mHealth has a market size of 107 billion EUR in 2021 and estimated to be 227 billion EUR by 2025 (Statista, 2023a)), namely, gamified smartphone health and fitness apps. The latter experienced a 45% boost in health and fitness app users since the Covid-19 in users; in total, there are estimated 385 million users as of 2022 (Business of Apps, 2023).

Concerning acceptance and adoption, little is known about the antecedents of consumers' acceptance and usage intentions of gamified smartphone health and fitness apps for physical activity. In other various contexts, the second version of the Unified Theory of Acceptance and Use of Technology (UTAUT2) has been developed to explain consumers' acceptance of new technology (Venkatesh et al., 2012). However, in the context of gamified smartphone health and fitness apps, previous studies have ignored essential determinants that the UTAUT2 incorporates (e.g., habit and hedonic motivation). In addition, the downstream associations between intentions of using fitness health and apps and intentions of being physically active have not been explored. Most importantly, there lacks of an understanding of whether different smartphone health and fitness app features, particularly gamification-related features, may be moderating the relationships of the UTAUT2 determinants and behavioral intentions of using the apps. For example, the gamification-related app features may enhance the playfulness and enjoyment of user experience, which might explain the rather modest effects on the effects of fitness apps on physical activity found in previous reviews (Romeo et al., 2019). Study 1 aims to partially fill these research gaps.

In addition, the world faces a significant external shock of the Covid-19 since 2019. The emergence of the Covid-19 pandemic and the associated restricting regulations have compelled individuals to disrupt their normal physical activity routines and they had fewer opportunities for outdoor activities during this time. As such, consumer wearables or smartphone health and fitness apps (e.g., with the aim to help people perform indoor activities alone) may be particularly useful in helping people remain physically active during Covid-19 (Chen et al., 2020). In particular, these smartphone health and fitness apps that don't necessitate the acquisition of new equipment offer cost-effective means to encourage physical activity, given that users remain committed to using the apps (Romeo et al., 2019). However, at the beginning of Covid-19, there was limited evidence suggesting whether consumers' physical activity levels have changed during the Covid-19 pandemic, and no evidence on whether smartphone health and fitness app use helped prevent declines in physical activity. Furthermore, the role of gamification-related app features was unclear. Study 2 utilizes a two-wave longitudinal survey design (i.e., before and during the Covid-19 measures in 2020) to partially fill these research gaps.

When talking about the effectiveness, there lacks systematic literature reviews and meta-analyses that assess the effects of standalone gamified smartphone health and fitness apps on physical activity. The focus on the standalone gamified smartphone health and fitness apps (i.e., without the need for additional supervision or assistance) and exclusive app utilization (i.e., without additional intervention methods) is crucial, because this is typically how consumers use their apps in their daily lives. In addition, the assessment of the cause-and-effect relationships of gamified smartphone health and fitness apps on physical activity without any confounds is possible. However, none of the previous literature reviews focused on the standalone effects of gamified smartphone health and fitness apps, namely, from a perspective of consumers' daily usage (e.g., (González-González et al., 2018; Hamari, 2019; Johnson et al., 2016; Laranjo et al., 2021; Mazeas et al., 2022; Tabak et al., 2015)). Study 3 aims to partially fill this research gap.

1.1. Research questions and aims

The three studies in this dissertation aim to investigate the role of gamified smartphone health and fitness apps for physical activity, concerning consumers' acceptance and adoption of these apps as well as their effectiveness. Specifically, Study 1 aims to answer the following four research questions:

(i) *What are the relationships between the UTAUT2 determinants (i.e., performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit) and individuals' behavioral intentions of using smartphone health and fitness apps?*

(ii) *What is the downstream relationship between behavioral intentions of using smartphone health and fitness apps and intentions of being physically active?*

(iii) *Do smartphone health and fitness app features (gamification, education, and motivation related) moderate the relationships between the UTAUT2 determinants and intentions of using these apps?*

(iv) *Are there individual differences regarding age, gender, and user experience in the relationships between the UTAUT2 determinants and intentions of using smartphone health and fitness apps?*

Study 2 aims to investigate the change in consumers' physical activity during the Covid-19 lockdown and the determinants of the maintenance of physical activity, by focusing on the gamified smartphone health and fitness apps. The research is guided by the following three research questions:

(v) *Did physical activity levels change during Covid-19-caused lockdown?*

(vi) *Did the use of smartphone health and fitness apps help individuals remain physically active during Covid 19-caused lockdown?*

(vii) *Which smartphone health and fitness app features supported individuals in remaining physically active during Covid-19-caused lockdown?*

Study 3 aims to synthesize the evidence of the effects of standalone gamified smartphone health and fitness apps on physical activity, summarize the implemented gamification elements within the apps, and hence provide implications for future research.

1.2. Research significance

The three studies of this dissertation advance the understanding of the important role of gamification in smartphone health and fitness apps for consumers' physical activity intentions and behaviors. Theoretically, this dissertation addresses the key drivers of consumers' acceptance and adoption of smartphone health and fitness apps by assessing the moderating role of gamification-related app features (Study 1 proposes and tests a positive interaction effect of gamification-related app features and hedonic motivation on behavioral intentions of using health and fitness apps), longitudinally testing the effects of gamified smartphone health and fitness apps on physical activity during the external shock of Covid-19 (Study 2), and systematically and quantitatively synthesizing the evidence of the effects of standalone gamified smartphone health and fitness apps on physical activity (Study 3). The findings provide insightful theoretical and practical perspectives for future research, concerning the nuanced effects of specific gamification design elements on consumers’ health intentions and behavior.

2. Theoretical Background and Literature Review

This section introduces the concepts of the UTAUT2, gamification, smartphone health and fitness apps, and physical activity. The section also discusses the suitability of employing the UTAUT2 as the theoretical framework to elucidate the impact of smartphone health and fitness apps in general and gamification elements in particular on physical activity. Further, the literature on the determinants of smartphone health and fitness apps' acceptance and usage and determinants of physical activity maintenance is briefly reviewed.

2.1. The UTAUT2 and its suitability to explain the influence of smartphone health and fitness applications in general and gamification elements in particular on physical activity

In 1986 in his doctoral dissertation, Davis introduced the Technology Acceptance Model (TAM, (Davis, 1989)) based on the work of Ajzen and Fishbein's Theory of Reasoned Action. The latter provides a fundamental understanding that consumers' decision-making of technology consumption is driven by two constructs: attitude toward behavior and subjective norm. The TAM suggests that people's intentions to accept or reject information technology are mainly determined by two constructs, namely, perceived usefulness and perceived ease of use (Davis, 1989). The TAM has been the most widely used theoretical framework to explain users' adoption of technology, among various contexts such as education, business, and health (Marangunić & Granić, 2015).

In 2003, Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT) by unifying seven core constructs of eight previously established theories. These eight theories are the Theory of Reasoned Action, TAM, Motivational Model, Theory of Planned Behavior, Combined Technology Acceptance Model and Theory of Planned Behavior Model, Model of PC Utilization, Diffusion of Innovation Theory, and Social Cognitive Theory. The UTAUT proposes that performance expectancy, effort expectancy, social influence, and facilitating conditions are the four key determinants of the behavioral intentions of acceptance and usage behaviors of technology. Furthermore, the UTAUT emphasizes the importance of the moderating role of individual differences such as age, gender, experience, and voluntariness of usage (Venkatesh et al., 2003). Yet, both the TAM and UTAUT focus on organizational contexts.

In 2012, the second version of the UTAUT (i.e., UTAUT2) was proposed. The authors identified three additional factors compared to the previously described UTAUT: hedonic motivation, price value, and habit (Venkatesh et al., 2012), to explain individuals' acceptance of new technology in a consumer setting. Similar to the UTAUT, the UTAUT2 empirically investigates the moderating effects of age, gender, and experience on the relationships between UTAUT2 determinants and behavioral intentions. In particular, the definitions of the core constructs of the UTAUT2 are provided as follows. *Performance expectancy* refers to the "degree to which using a technology will provide benefits to consumers in performing certain activities" ((Venkatesh et al., 2012), same below; p. 159), which is similar to the *perceived usefulness* in the TAM. *Effort expectancy* refers to "the degree of ease associated with consumers' use of technology" (p. 159), similar to the *perceived ease of use* as described in the TAM. *Social influence* refers to "the extent to which consumers perceive that important-others (e.g., friends, peers) believe they should use a particular technology" (p. 159). *Facilitating conditions* refer to "consumers' perceptions of the resources and support available to perform a behavior" (p. 159). *Price* *value* refers to “consumers’ cognitive trade-off between the perceived benefits of a technology and the monetary cost of using it” (p. 161). *Hedonic motivation* refers to “the fun or pleasure derived from using a technology” (p. 161). *Habit* refers to “the extent to which people tend to perform behavior automatically”, and was found to be a positive predictor of behavioral intentions of using the mobile Internet (p. 161). The UTAUT2 suggests that all seven constructs are important drivers of consumers’ behavioral intention of using mobile Internet, as well as actual usage behaviors (Venkatesh et al., 2012).

Smartphone is one of the prominent mobile Internet devices. Today, there are over 5 billion smartphone users worldwide (Statista, 2023b), and consumers heavily rely on their smartphones, for several reasons. Some researchers even consider smartphones as psychological pacifying tools (Melumad & Pham, 2020). Consequently, numerous smartphone apps have been developed for the purpose of satisfying users’ social media- and gaming-related needs, as well as managing one’s health and fitness. In the category of *Health and Fitness* apps, there are 93,396 (3.9% of the total) apps are available to users in the Google Play Store (AppBrain, 2023) and 174,814 (3.6% of the total) apps in the Apple App Store (PocketGamer, 2023). These apps seem promising in enhancing consumer physical activity and health motivations and behaviors (James et al., 2019; Soulé et al., 2022; Yerrakalva et al., 2019). Importantly, the market size of smartphone apps is estimated to reach $15.2 Billion by 2028 (Newswire, 2022).

Building upon the context of mobile Internet consumers (Venkatesh et al., 2012), the UTAUT2 is inherently suitable to explain the influence of smartphone health and fitness apps on physical activity. In fact, since the UTAUT2’s first application, it has been used to explain consumers' smartphone apps' adoption and usage behaviors (e.g., (Duarte & Pinho, 2019; Venkatesh et al., 2016)), among other applications. For example, prior research employed the UTAUT2 framework to explore the determinants of behavioral intentions of using fitness-promoting smartwatches (Beh et al., 2019; Mishra et al., 2023) and fitness apps (Yuan et al., 2015). Yet, none of them considered the gamified smartphone health and fitness apps and the individual difference factors as moderators on the proposed relationships. Therefore, the key research question remains: what factors influence consumers' adoption of the gamified smartphone health and fitness apps for physical activity, and what are the subsequent relationships with intentions to engage in healthy behaviors?

More specifically, the UTAUT2 is suitable to explain the influence of smartphone health and fitness apps incorporated with particular gamification elements on physical activity. The concept of gamification origins from existing research on game, playful design, and users' enjoyable experience (Deterding et al., 2011). As suggested by the UTAUT2, the hedonic motivation (i.e., the enjoyment or satisfaction derived from utilizing technology) is a crucial determinant of consumers' acceptance and usage of technology (Venkatesh et al., 2012). When integrating gamification elements into the smartphone health and fitness apps, these gamified apps aim to enhance users' hedonic motivation of acceptance and usage intentions, by creating a fun and enjoyable interaction with consumers. However, little to no studies have examined consumers' acceptance and usage in the context of gamified smartphone health and fitness apps, from a theoretical perspective of the UTAUT2 (e.g., Al Katheeri et al., 2023).

2.2. Determinants of smartphone health and fitness application acceptance and usage

Smartphone health and fitness apps refer to those apps that are "related to healthy living, including stress management, fitness, and recreational activities" (*Apple App Store*; apple.com) and related to "personal fitness, workout tracking, diet and nutritional tips, health and safety" (*Google Play Store*; google.com). Consumers' acceptance and usage intentions of the health and fitness apps is an important issue since they are only effective if consumers accept and continually use these apps to motivate themselves to become or maintain physically active. From a theoretical perspective, there are various factors influencing consumers' acceptance and usage intentions of the smartphone health and fitness apps. Also, there are important moderators of the relationship, arguing for target group- or context-specific effects. This contributes to the complexity of drawing a full picture of the determinants of consumers' acceptance and usage intentions of smartphone health and fitness apps. A recent literature review summarized 13 studies and identified several theoretical frameworks in explaining the drivers of intentions to use fitness and physical activity apps, such as the Theory of Readiness and Acceptance Model and Expectation-Confirmation Model (Angosto et al., 2020). Other theories are also applied, such that Q. Aldossari et al. (2022) identified that system quality and information quality are important determinants of fitness app users' physical activity goal setting and goal tracking behavior, based on the goal setting theory.

However, the most widely used theoretical frameworks to explain consumers' smartphone health and fitness application acceptance and usage are the TAM (Davis, 1989), UTAUT (Venkatesh et al., 2003), UTAUT2 (Venkatesh et al., 2012), or integrated models of these theories (Angosto et al., 2020). Based on the UTAUT2, Beh et al. (2019) found positive associations between performance expectancy, effort expectancy, facilitating conditions, as well as hedonic motivation and behavioral intentions of using smartwatches for fitness and health monitoring purposes. Dhiman et al. (2019) found that effort expectancy, social influence, price value, and habit related positively to fitness app adoption intentions. They also regarded self-efficacy as a predictor of effort expectancy and innovativeness as a predictor of habit. Damberg (2022) extended the UTAUT2 to explain the drivers of future intention to use fitness apps by considering additional health consciousness, and found that habit, perceived playfulness, health consciousness, perceived performance and price value explain future use intention. Yuan et al. (2015) did not incorporate any mediating factors in their study and found that performance expectancy, hedonic motivation, price value, and habit were predictors of behavioral intentions of continuously using health and fitness apps, but that effort expectancy, social influence, and facilitating conditions were non-significant predictors.

These studies have notable limitations. First, none of them evaluated the downstream effects on intentions of being physically active. The path of the intentions to use smartphone health and fitness apps and intentions to be physically active is crucial, since the health benefits can only be realized if the intended app usage effectively motivates individuals to initiate or maintain physical activity. Second, none of the studies took into account app features as potentially significant moderators, despite the fact that previous research considered app types (game, social, productivity) that might moderate the effects of UTAUT2 determinants on app usage intentions (e.g., the relation between performance expectancy and app usage intention was stronger for productivity apps

(Peng et al., 2018)). Third, only one study assessed the moderating role of individual differences, and it found that age, gender, and experience were all non-significant factors in the model and hence excluded them without further explanation (Yuan et al., 2015). However, these individual differences play significant moderating role in technology acceptance (e.g., age (Niehaves & Plattfaut, 2014), gender (Venkatesh & Morris, 2000), and experience (Sun & Zhang, 2006)). Thus, important similarities with, and differences to, the original UTAUT2 studies as regards the influence of individual differences (e.g., age, gender, and experience) remain largely unknown.

2.3. Determinants of physical activity maintenance

Physical activity is defined as “any bodily movement that generates energy expenditure” ((Caspersen et al., 1985), p.126). While the health benefits of being physically active have been well-evidenced (Bull et al., 2020; Ekelund et al., 2019), physical inactivity is one of the leading risk factors for death and one in four adults worldwide have insufficient physical activity levels (World Health Organization, 2023). The World Health Organization recommends adults do 150 to 300 minutes of moderate physical activity or 75 to 150 minutes of vigorous physical activity per week, or an equivalent combination of these two activities throughout the week (World Health Organization, 2023).

The various determinants for physical activity maintenance have been extensively explored (Bauman et al., 2012; Ding et al., 2020). For example, people’s physical activity levels are partly determined by the social and physical environment (e.g., urban planning, transportation systems, and parks and trails) (Bauman et al., 2012). Also, their physical activity maintenance is shaped by complex psychosocial factors (e.g., self-efficacy, personality, and motivation) and socio-demographics (e.g., age, sex, and health status) (Bauman et al., 2012; Kekäläinen et al., 2022). A systematic literature review of the determinants of physical activity maintenance further emphasized the psychosocial contributors such as social influence, goal setting, and health beliefs (Amireault, Godin, & Vezina-Im, 2013).

Maintaining physical activity during Covid-19 was particularly important, since the global outbreak of Covid-19 has further decreased people's physical activity levels (Tison et al., 2020). Covid-19 compelled governments to implement various restrictions (such as closures of businesses, schools, and factories, border closures to restrict travel, and the implementation of social distancing rules) in order to mitigate the spread of the disease. As a result, these restrictions may have disrupted people's regular physical activity routines and resulted in physical inactivity. For example, Spence et al. (2021) investigated the influence of Covid-19 lockdown on UK adults' physical activity and suggested that physical activity opportunity and reflective motivation are the most consistent predictors.

The use of health and fitness apps seems effective in maintaining physical activity levels. Yet, there is limited understanding concerning which app features may help people remain physically active. Previous research has cluster-analyzed physical activity apps and found two broad features: motivational (e.g., feedback, social support, and goal setting) and educational (e.g., instructions, coaching, and learning) app features (Conroy et al., 2014). In addition, gamification-related features are increasingly being integrated into physical activity apps as a means to improve individuals' health and fitness (Lister et al., 2014).

2.4. Gamified smartphone applications for physical activity

Gamification is a research topic that has been prominently incorporated in various fields, and one of the most widely accepted definitions is that “gamification is the use of game design elements in non-game contexts” ((Deterding et al., 2011), p.1). Typical gamification elements (or affordances (Koivisto & Hamari, 2019)) include points, badges, levels, leaderboards, avatar, competition, and team cooperation. These elements can be categorized into three types, namely, achievement-related, social-related, and immersion-related elements. Gamification has been shown to be relevant in various research fields, including marketing, innovation, consumer behavior, and information systems (Liu et al. (2017). For example, gamified interactions facilitate consumer-brand connections (Berger et al., 2018) and gamified information presentation increases the adoption of product innovations (Müller-Stewens et al., 2017). Several studies focus on specific gamification elements and provide evidence for the antecedents of gamification as well as the downstream relation with management-relevant outcome variables. For example, competition, one of the important gamification elements, is driven by different skill levels of competitors (Liu et al., 2013; Santhanam et al., 2016). Other gamification elements, such as points and badges, are effective in encouraging consumers’ word-of-mouth behavior, in particular online reviews (Wang et al., 2017). In a recent review, over 47 different gamification elements have been identified.

“Health & Fitness” is an area where gamification might be particularly helpful, because consumers need to be continuously motivated to become active, and gamified elements might help consumers to do so (Koivisto & Hamari, 2019). In the context of the current dissertation, I explicitly focus on the use of gamification in smartphone health and fitness apps for physical activity. Gamification features have been implemented in health and fitness apps (Cotton & Patel, 2019; Edwards et al., 2016; Lister et al., 2014), including the features to boost user motivation, particularly intrinsic motivation (e.g., the joy of engaging in the activity itself), and sustain long-term physical activity habits (King et al., 2013).

3. Methodology

3.1. Overview of research approach

The current dissertation utilizes a mixed methods approach, including cross-sectional survey design (Study 1), two-wave longitudinal survey design (Study 2), and systematic literature review and meta-analysis (Study 3). In the following, the detailed methodological approach including study design, sample, measure, and statistical analysis are illustrated. **Table 1** provides an overview of the characteristics of the three studies.

Table 1. Overview of study characteristics.

	Study 1	**Study 2**	**Study 3**
Purpose	To examine the determinants of consumers' smartphone health and fitness app usage intentions and their behavioral intentions of being physically active, by focusing on the moderating effects of gamification app features.	To investigate the change in physical activity during the Covid-19-caused lockdown and the determinants for the maintenance of physical activity, by focusing on the gamified smartphone health and fitness apps.	To systematically review the literature and quantitively synthesize the evidence of the effects of standalone gamified smartphone health and fitness apps for physical activity.
Design	Cross-sectional survey	Longitudinal survey	Systematic review and meta-analysis
Sample	*N* = 839, U.S.	*N* = 431, U.S.	Pooled *N* = 1,908, multiple countries
Measured constructs	Performance expectancy; effort expectancy; social influence; facilitating conditions; hedonic motivation; price value; habit; motivation-, education-, and	Physical activity levels; intentions of being physically active; smartphone app features; usage of fitness apps	NA

	gamification-related app features; behavioral intentions to use fitness app; intentions of being physically active		
Statistical analysis	Structural equation modeling, path analysis	Ordinary least squares linear regressions	Meta-analysis, meta-regression, subgroup and sensitivity analyses

Note. NA: Not Applicable.

The three studies of this dissertation adhered to the ethical standards of the Faculty of Sport and Health Sciences and School of Management at the Technical University of Munich, and with the 1964 Helsinki declaration and its subsequent amendments or equivalent ethical standards. All the data analyses in this dissertation were performed with R (RStudio, Boston, MA, USA), and the level of significance was set at $P < 0.05$ (two-tailed).

3.2. Study 1

Study 1 applied a cross-sectional online survey design. In total, 867 Amazon Mechanical Turk workers (i.e., U.S. residents) were recruited in 2020. They were healthy adults between 18 and 65 years old, owned a smartphone, and had downloaded at least one smartphone fitness app before. The reliability and utility of Amazon Mechanical Turk as a platform for conducting behavioral research have been previous evidenced (Goodman et al., 2013; Mason & Suri, 2012).

The survey consisted of questions about UTAUT2-related constructs, mediators and moderators, as well as demographics of participants, which were collected towards the end of the survey. The UTAUT2-related items for the seven determinants and behavioral intentions of using smartphone health and fitness apps were adapted from Venkatesh et al. (2012) to suit the context of this study. A seven-point rating scale ranging from 1 (strongly disagree) to 7 (strongly agree) was employed to measure these constructs. Behavioral intentions of being physically active were measured using a single question from Biddle et al. (1999). Individual difference variables, including age, gender, and experience, were self-reported. All three app features were measured via three items each, among which, gamification-related app features were operationalized based on existing literature on gamification and fitness apps (Koivisto & Hamari, 2019).

To evaluate the internal reliability, convergent validity, and discriminant validity of the measurement model, a confirmatory factor analysis was conducted, utilizing various model fit indices (Anderson & Gerbing, 1988). Hypotheses tests were performed with path modeling (*maximum likelihood estimation*). Prior to the analysis, the variables were mean-centered, and gender was coded as a dummy variable (0 = female, 1 = male). Where significant interaction effects were observed between UTAUT2 determinants and app features, follow-up tests were conducted to observe how the moderator influences the hypothesized relationships. The path modeling was performed with R package *lavaan* (Rosseel, 2012).

3.3. Study 2

Study 2 employed a two-wave longitudinal survey design, also delivered via Amazon Mechanical Turk. The inclusion criteria of participants were similar to Study 1. The data collection for the first-wave (T0) took place between March 12 and 17, 2020, a period when no Covid-19 restricting regulations (e.g., stay-at-home order) were imposed at the U.S. state level. The second wave of the survey (T1) took place after the U.S.

government and the states responded to the Covid-19 pandemic by implementing restrictive measures to slow its spread, and after these restrictions had been in place for at least four weeks (e.g., ensuring an adequate response to Covid-19, and aligning with the time frame of the app usage and physical activity questionnaire described below). The average time interval between T0 and T1 was 43.7 days (SD = 4.7). The final sample size was N = 431 (i.e., 48% bigger than the minimum recommended sample size determined by an a-priori power analysis using G*Power Version 3.1 (to allow for the inclusion of control variables in the analyses).

Physical activity was measured at both T0 and T1 using the International Physical Activity Questionnaire Short Form (IPAQ-SF) (Craig et al., 2003). To measure individuals' intentions to be physically active at T0, similar items as the IPAQ-SF items (covering a time span of four weeks into the future) were used. Participants were asked to indicate their preferred smartphone health and fitness app and provide their perceptions of the features offered by that specific app. Educational, motivational, and gamification-related app features were measured using a nine-item scale (three items each). Participants rated the importance of these app features on a scale ranging from 1 (not at all important) to 7 (extremely important). The usage of smartphone health and fitness apps was assessed by capturing the frequency of use during the past four weeks (Venkatesh et al., 2012).

Paired samples t-tests were conducted to compare the differences between T0 and T1. Three ordinary least squares linear regression analyses were performed to predict the maintenance of physical activity during the Covid-19 lockdown. The dependent variable was the change in physical activity (T1 - T0, denoted as Y in the regression equation, measured in MET-min/week). The independent variables included physical activity app use measured at T1 (X in the regression equation, measured as frequency of use in the past four weeks), physical activity measured at T0, individuals' intentions to be physically active measured at T0. Control variables were physical activity app features (i.e., motivational, educational, and gamification-related; measured on rating scales), age (years), gender (dummy, 0 = female), body mass index (kg/m^2), education (dummy, four categories), income (dummy, five categories), marital status (dummy, three categories), employment (dummy, two categories), and ethnicity (dummy, three categories). The results were reported following the CHERRIES statement for web-based surveys (Eysenbach, 2004).

3.4. Study 3

Study 3 followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines (PRISMA, (Page et al., 2021)) and the Cochrane Collaboration handbook (Higgins et al., 2019). The review protocol for this study was registered with PROSPERO (CRD42020209502). A systematic search was conducted across five databases (Web of Science, Scopus, PubMed, PsycINFO, and ACM Digital Library) until August 31, 2021. The publication year was restricted to the period beginning in 2008, when the term "gamification" emerged in the literature (Deterding et al., 2011). The search focused on peer-reviewed journal articles or conference papers with English full texts. The search string consisted of 3 groups of keywords: gamification, smartphone app, and physical activity. This review included studies based on the predetermined Population, Intervention, Comparison, Outcomes, and Study (PICOS) design criteria (Higgins et al., 2019).

Two researchers (Y.Y. and H.H.) excluded the duplicates of the eligible articles, screened the titles, abstracts, and full texts, and extracted the information of the included studies. Any disagreements were resolved through discussion with the third researcher (J.K.) until a consensus was reached. Similarly, two reviewers (Y.Y. and H.H.) independently evaluated the risk of bias and resolved any disagreements through consensus with an additional reviewer (J.K.). The Risk of Bias 2 (Sterne et al., 2019) was used for the randomized control trials (RCTs, n = 17), and the Risk of Bias in Non-randomized Studies–of Interventions (Sterne et al., 2016) was used for the single-arm pre-to-post interventions (n = 2). Moreover, the gamification features employed in the smartphone health and fitness apps were extracted based on an established framework of features (Koivisto & Hamari, 2019). In particular, the present study considered core gamification features of the achievement (e.g., leaderboards, rankings, points, and scores), immersion (e.g., storytelling, use of avatars), and leveraging gamification (e.g., prompts/cues, goal setting) features.

The meta-analyses were performed for the between-group (e.g., differences between intervention and control groups for the RCTs) and the within-group (e.g., changes from pre-to-post interventions among all the intervention groups. For the main results, standardized mean differences (SMDs) were computed from different physical activity outcomes and units. Various estimate indices were calculated including the Hedge's g values (Higgins et al., 2019), statistical heterogeneity of I^2 values (Higgins et al., 2019), and publication bias by Egger's test (Egger et al., 1997). Furthermore, meta-regression, subgroup, and sensitivity analyses were conducted. The levels of evidence for the primary outcomes were assessed using the Grading of Recommendations

Assessment, Development and Evaluation (GRADE) guidelines (Guyatt et al., 2011). The meta-analysis was conducted with the R package *meta* (Schwarzer & Schwarzer, 2012).

4. Essays

4.1. Essay 1: Determinants of fitness app usage and moderating impacts of education-, motivation-, and gamification-related app features on physical activity intentions: Cross-sectional survey study

Publication (peer reviewed): **Yang, Y.**, & Koenigstorfer, J. (2021). Determinants of fitness app usage and moderating impacts of education-, motivation-, and gamification-related app features on physical activity intentions: Cross-sectional survey study. *Journal of Medical Internet Research*, 23(7), e26063. DOI: 10.2196/26063

Main Author: Yanxiang Yang

Author contributions: Y.Y. contributed to the study design, data collection, processing, and analysis and wrote the first draft. J.K. contributed to the study design, data analysis, and edited drafts and served as the principal investigator of this study.

Abstract:

Background: Smartphone fitness apps are considered promising tools for promoting physical activity and health. However, it is unclear which user-perceived factors and app features encourage users to download apps with the intention of being physically active.

Objective: Building on the second version of the Unified Theory of Acceptance and Use of Technology, this study aims to examine the association of the seven determinants of the second version of the Unified Theory of Acceptance and Use of Technology with the app usage intentions of the individuals and their behavioral intentions of being physically active as well as the moderating effects of different smartphone fitness app features (i.e., education, motivation, and gamification related) and individual differences (i.e., age, gender, and experience) on these intentions.

Methods: Data from 839 US residents who reported having used at least one smartphone fitness app were collected via a web-based survey. A confirmatory factor analysis was performed, and path modeling was used to test the hypotheses and explore the influence of moderators on structural relationships.

Results: The determinants explain 76% of the variance in the behavioral intention to use fitness apps. Habit ($\beta = 0.42$; $P < 0.001$), performance expectancy ($\beta = 0.36$; $P < 0.001$), facilitating conditions ($\beta = 0.15$; $P < 0.001$), price value ($\beta = 0.13$; $P < 0.001$), and effort expectancy ($\beta = 0.09$; $P = 0.04$) were positively related to behavioral intention to use fitness apps, whereas social influence and hedonic motivation were nonsignificant predictors. Behavioral intentions to use fitness apps were positively related to intentions of being physically active ($\beta = 0.12$; $P < 0.001$; $R^2 = 0.02$). Education-related app features moderated the association between performance expectancy and habit and app usage intentions; motivation-related features moderated the association of performance expectancy, facilitating conditions, and habit with usage intentions; and gamification-related features moderated the association between hedonic motivation and usage intentions. Age moderated the association between effort expectancy and usage intentions, and gender moderated the association between performance expectancy and

habit and usage intentions. User experience was a nonsignificant moderator. Follow-up tests were used to describe the nature of significant interaction effects.

Conclusions: This study identifies the drivers of the use of fitness apps. Smartphone app features should be designed to increase the likelihood of app usage, and hence physical activity, by supporting users in achieving their goals and facilitating habit formation. Target group–specific preferences for education-, motivation-, and gamification-related app features, as well as age and gender differences, should be considered. Performance expectancy had a high predictive power for intended usage for male (vs female) users who appreciated motivation-related features. Thus, apps targeting these user groups should focus on goal achievement–related features (e.g., goal setting and monitoring). Future research could examine the mechanisms of these moderation effects and their long-term influence on physical activity.

4.2. Essay 2: Determinants of physical activity maintenance during the Covid-19 pandemic: A focus on fitness apps

Publication (peer reviewed): **Yang, Y.**, & Koenigstorfer, J. (2020). Determinants of physical activity maintenance during the Covid-19 pandemic: A focus on fitness apps. *Translational Behavioral Medicine*, 10(4), 835-842. DOI: 10.1093/tbm/ibaa086

Main Author: Yanxiang Yang

Author contributions: Y.Y. contributed to the study design, data collection, processing, and analysis and wrote the first draft. J.K. contributed to the study design, data analysis, and edited drafts and served as the principal investigator of this study.

Abstract:

There are various health benefits of regular physical activity (PA) and health risks of sedentariness. The Covid-19 pandemic may have decreased PA and increased sedentariness for several reasons (e.g., closure of gyms, family-related time constraints, and reduced outdoor mobility). Yet, to date, there are no longitudinal studies that examined whether the pandemic affects PA levels and what factors help people remain physically active during lockdown. This study aims to investigate changes in U.S. residents' PA during (vs. before) the Covid-19 pandemic and predictors of changes, with a focus on PA smartphone applications (apps) and their features (i.e., motivational, educational, or gamification related). The study utilized a two-wave longitudinal survey design with an online panel. Healthy adults (N = 431) from 45 U.S. states self-reported their PA levels before and during lockdown. PA app use and app feature ratings were assessed. t-tests and regression analyses were conducted. Moderate PA, vigorous PA, and PA measured in metabolic equivalent of task (MET) minutes per week decreased during lockdown (all $P < 0.01$). Controlling for PA before lockdown and individuals' PA intentions, PA app use was positively related to overall change in PA, measured in MET minutes per week (β = 15.68, standard error = 7.84, $P < 0.05$). PA decreased less with increasing app use frequency. When app features were added to the model, a buffering effect for gamification features was identified. The Covid-19-caused lockdown decreased U.S. residents' PA levels by 18.2%. The use of PA apps may help buffer the decline, and gamification-related app features may be particularly helpful in this context.

4.3. Essay 3: Effects of gamified smartphone applications on physical activity: A systematic review and meta-analysis

Publication (peer reviewed): **Yang, Y.**, Hu, H., & Koenigstorfer, J. (2022). Effects of gamified smartphone applications on physical activity: A systematic review and meta-analysis. *American Journal of Preventive Medicine*, 62(4), 602-613. DOI: 10.1016/j.amepre.2021.10.005

Main Author: Yanxiang Yang

Author contributions: Y.Y.: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Writing - original draft. H.H.: Methodology; Investigation. J.K.: Conceptualization; Investigation; Methodology; Project administration; Resources; Supervision; Writing - review & editing.

Abstract:

Introduction: This systematic review and meta-analysis aims to examine the impacts of standalone gamified smartphone application-delivered interventions on physical activity.

Methods: Web of Science, Scopus, PubMed, PsycINFO, and ACM Digital Library were searched for publications that were published between January 1, 2008 and August 31, 2021. Eligibility criteria were RCTs or single-arm pre-to-post interventions delivered by standalone gamified applications and targeting physical activity. Study-specific results were analyzed using random-effects meta-analysis, with a standardized mean difference. Meta-regressions, subgroup analyses, and sensitivity analyses were performed. PRISMA guidelines were followed, and the Grading of Recommendations Assessment, Development and Evaluation system was used to determine the strength of the evidence.

Results: A total of 19 studies with 24 gamified applications were eligible, and 16 studies were included in the meta-analysis. Standalone gamified applications had a small-to-moderate effect on physical activity in both the between-group RCTs (n = 12 applications, standardized mean difference = 0.34, 95% CI = 0.06, 0.62, $I^2 = 72\%$, $P < 0.01$; Grading of Recommendations Assessment, Development and Evaluation: moderate) and the within-group pre-to-post interventions (n = 18 applications, standardized mean difference= 0.38, 95% CI = 0.17, 0.59, $I^2 = 74\%$, $P < 0.01$; Grading of Recommendations Assessment, Development and Evaluation: very low). Leave-one-out sensitivity analyses sustained the main effects with lower heterogeneity (I^2 of 31.0% and 47.8%, respectively).

Discussion: Using gamified smartphone applications as standalone interventions may increase physical activity. Future research could investigate the impacts of gamified applications on physical activity by isolating the role of specific single or clustered groups of application features.

5. Findings and General Discussion

In this section, the main findings of the three studies are summarized, and the theoretical and managerial implications are discussed.

5.1. Main findings

By applying and extending the UTAUT2, the determinants explain 76% of the variance in behavioral intentions of using fitness apps in Study 1. The findings show that habit and performance expectancy are the two strongest predictors of consumers' intentions to use fitness apps. The effect of performance expectancy is amplified when motivation-related features are rated important and education-related features are considered less significant, as well as for males. On the other hand, the effects of habit are heightened when education-related features are rated as important and motivation-related features are viewed as less important, as well as for females. Age negatively moderates the relationship between effort expectancy and app usage intentions. Importantly, when gamification-related features are regarded as important, the association between hedonic motivation and usage intentions becomes stronger but remains non-significant compared to when this feature is considered unimportant. Furthermore, individuals' intentions to use fitness apps predict their intentions to engage in physical activity.

Study 2 regresses the determinants of physical activity maintenance during the Covid-19 lockdown and the model explains 38% of the variance in the change in physical activity. The results show a significant decrease of 18.2% in moderate and vigorous physical activity levels during the Covid-19 lockdown. However, using smartphone health and fitness apps may help buffer the decline in physical activity, such that the more often the app is used, the more positive is the change in physical activity levels. Most importantly, the results show that gamification-related app features may be particularly helpful, as an increasing perceived importance of these features is associated with a more positive change in physical activity levels.

The primary findings of Study 3 indicate that the utilization of gamified smartphone apps led to a significant increase in physical activity. Yet, the evidence level was determined to be moderate for randomized controlled trials (RCTs) and very low for pre-to-post interventions. The main effects are significantly modified by intervention duration (positive effects with increasing duration), sex (stronger for male [vs. female]), population (stronger effects for healthy people [*vs.* patients]), and physical activity outcomes (larger effects for step counts [*vs.* moderate-to-vigorous physical activity]). In addition, the study identifies twelve gamification features from 24 gamified apps of the 19 included literature. Among these features, in-game rewards and leaderboards are the most frequently implemented gamification elements.

5.2. Theoretical implications

Study 1 contributes to the mobile health and physical activity literature by extending the UTAUT2 in the contexts of smartphone health and fitness apps for physical activity, considering downstream effects of app usage intentions, the moderating role of gamification-related app features, as well as the influence of individual differences. The findings enhance our understanding of the determinants influencing the adoption and usage of smartphone health and fitness apps for physical activity. In particular, the findings shed light on the relationships between UTAUT2 determinants and intentions of using health and fitness apps, largely aligning with previous research contexts (e.g., Beh et al., 2019; Yuan et al., 2015), by answering the first research question (i.e., What are the relationships between the UTAUT2 determinants and intentions of using smartphone fitness apps?). In addition, this study contributes to UTAUT2-based research by showing that app usage intentions have important downstream consequences and app usage might indeed motivate people to become or remain active, by answering the second research question (i.e., What is the downstream relationship between behavioral intentions of using fitness apps and intentions of being physically active?). By answering the third research question (i.e., Do fitness app features moderate the relationships between the UTAUT2 determinants and intentions of using fitness apps?), the present study contributes to previous research that categorized app features (Conroy et al., 2014), yet ignored their influence on the structural relationships proposed by the UTAUT2. Furthermore, by answering the fourth research question (i.e., Are there individual differences regarding age, gender, and user experience between the relationships of the UTAUT2 determinants and intentions of using fitness apps?), the present study contributes to a deeper understanding of how these individual factors shape the relationships in the context of using mobile health and fitness apps to promote physical activity.

Study 2 partly fills the void of research into how the meaningful combination of gamification elements within smartphone health and fitness apps might help consumers maintain physical activity during the emergence of Covid-19. While previous studies have reported similar decreases in physical activity during Covid-19 (Zheng et al., 2020; Giustino et al., 2020; Lesser & Nienhuis, 2020; Gallo et al., 2020), these studies were largely cross-sectional in nature. In addition, while the determinants for physical activity maintenance have been extensively explored (Amireault, Godin, & Vézina-Im, 2013; Bauman et al., 2012), the role of gamified smartphone health and fitness apps has been largely overlooked. Most importantly, while there is research on the general effectiveness of physical activity apps (Direito et al., 2017; Romeo et al., 2019; Schoeppe et al., 2017), there are few answers to the question regarding which app features are effective to maintain physical activity. Hence, Study 2 contributes to this knowledge by highlighting the positive effects of gamification-related app features in facilitating physical activity maintenance during the Covid-19 lockdown. These findings enhance our understanding of the significance of app features in supporting individuals to sustain their physical activity levels during pandemics.

Study 3 is the first systematic review and meta-analysis to examine the effects of standalone gamified smartphone health and fitness apps on physical activity. Although other authors have conducted meta-analyses on the influence of app usage on physical activity, they did not specifically look at gamification and included not only apps, but also mobile health and fitness devices (e.g., trackers), as well as studies in which supervision and counseling were provided, beside app-based interventions (Laranjo et al., 2020; Mazeas et al., 2022). Therefore, Study 3 contributes to the literature by providing a comprehensive overview of the positive effects of standalone gamified smartphone health and fitness apps on physical activity in consumers' free-living conditions. Importantly, most of the gamified apps were designed with leaderboards, which allowed users to see each other's rank and current status. This was often accompanied by a social networking feature (i.e., a leveraging tool). Besides encouraging self-improvement, social features often created a competitive environment in which users could satisfy their motivational needs (e.g., achievement) (Tong & Laranjo, 2018). To further advance understanding in this field, future research may look into the nuanced effects of relative leaderboard positions for consumers, consider individual-differenced personality factors, and examine the specific leveraging factors within leaderboards (e.g., reinforcements) that contribute to their effectiveness.

5.3. Managerial implications

The three studies of this dissertation provide important implications for smartphone app consumers, designers, and managers, particularly emphasizing the role of gamification. For consumers, it is recommended to utilize these gamified health and fitness apps to effectively manage and maintain their physical activity and overall health, thereby reducing health risks and enhancing well-being (Study 1, 2, and 3). These recommendations hold true even during challenging times such as the Covid-19 pandemic, as evidenced by the findings from Study 2. Further, the findings imply that gamification (e.g., which element or groups of elements) or gamified systems (e.g., gamified apps, gamified interventions) should be tailored to consumers' health decision-making process and thereby foster their health behavior change.

Concerning the app designers, it is advisable to prioritize the integration of gamification elements, habit formation mechanisms, and performance-oriented features (e.g., goal-setting) when designing fitness apps. In addition, designers should aim to meet users' expectations in terms of facilitating conditions, price value, and effort expectancy, as this increases the likelihood of app acceptance and usage. It is also crucial for designers to consider age and gender differences among users, particularly in relation to the effects of effort expectancy (which tends to be stronger among younger individuals) as well as performance expectancy (which tends to be stronger among males) and habit (stronger among females).

With regards to health managers, gamification-related features might need to be implemented into the health promotion system to help engage individuals and encourage their continued app usage and physical activity. Health professionals should focus on incorporating specific core gamification elements, such as leaderboards and rewards, that effectively motivate individuals to both utilize the app and maintain a physically active lifestyle. By recognizing the potential of gamification and integrating it strategically, health managers can enhance the effectiveness of their health promotion initiatives.

6. Limitations and Outlook

The three studies in this dissertation have some limitations. Firstly, the generalizability of the findings is constrained. The participants of both studies 1 and 2 are non-representative sample of Amazon Turk workers: U.S. residents who owned a smartphone and have used fitness apps before and who work for the panel. Future studies may consider rather inexperienced consumers of gamified smartphone health and fitness apps to reveal the influence of UTAUT2 determinants on usage intentions at the early- or pre-adoption stage. Also, they may consider a different sample than Amazon Turk workers. In addition, there might be an issue with the lower attrition rate in Study 2 (i.e., only about half of the participants could be recruited in the second wave). Therefore, the results might be biased because individuals who could not be recruited again may have displayed different behaviors than individuals who completed in both waves.

Furthermore, both Study 1 and Study 2 rely on self-reported physical activity intentions using single measures (and partially in Study 3, of the included articles), which might be biased by overreporting. Previous research has highlighted notable differences between self-reported measures and objective assessments, which can arise due to various reasons such as biases and limitations in memory recall (Tucker et al., 2011). The same reasoning applies to the assessment of app usage. Therefore, the robustness of the findings from Study 1 and Study 2 should be tested using objectively measured physical activity levels as well as actual usage behavior of apps and their features in the future.

In Study 3, the pooled analyses revealed a significant level of heterogeneity, which can be attributed to the substantial variations in the measurement tools used to assess physical activity across the included studies. These differences in measurement methods may have introduced biases and contributed to the observed heterogeneity. Importantly, it is worth noting that most apps incorporated multiple gamification features. The underlying mechanisms of specific app features and their interactions should be investigated to identify those features that drive the effectiveness of gamified smartphone health and fitness apps. Although several important but under-researched gamification elements are identified, such as in-game rewards and leaderboards, the identification of these elements is limited to the elements used in the studies that were included in the systematic review and meta-analysis. Future gamification research could extend the list based on theoretical arguments and investigate the isolated role of specific single or clustered groups of gamification features.

7. Conclusions

Gamification plays an important role in mobile health. The dissertation contributes to the theories of gamification in technology acceptance and consumer behavior in the contexts of mobile health, with two empirical studies and one quantitative review study. The dissertation also offers outlook for future research such as investigating individual user experiences, and the isolated role of specific single or clustered groups of gamification features in consumer behavior research. To date, the smartphone health and fitness apps have been developing towards highly immersive and gamified, with virtual and augmented reality (e.g., the *Meta* bought VR fitness app *Supernatural* in 2023 and added VR fitness app *Liteboxer* to *Oculus Quest 2*). Hence, future research should take a comprehensive approach to understand the role of gamification in mHealth and the associated consumer behavior, such as considering potential drawbacks such as user fatigue or addiction (both due to excessive immersion), and exploring the applicability of gamification to various lifestyle related health behaviors beyond physical activity (e.g., smoking, alcohol consumption, healthy diet).

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Appendix

Essay 1

Essay 2

Essay 3

Essay 1

Copyrights and Permissions:

Original Paper

Determinants of Fitness App Usage and Moderating Impacts of Education-, Motivation-, and Gamification-Related App Features on Physical Activity Intentions: Cross-sectional Survey Study

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Abstract

Background: Smartphone fitness apps are considered promising tools for promoting physical activity and health. However, it is unclear which user-perceived factors and app features encourage users to download apps with the intention of being physically active.

Objective: Building on the second version of the Unified Theory of Acceptance and Use of Technology, this study aims to examine the association of the seven determinants of the second version of the Unified Theory of Acceptance and Use of Technology with the app usage intentions of the individuals and their behavioral intentions of being physically active as well as the moderating effects of different smartphone fitness app features (ie, education, motivation, and gamification related) and individual differences (ie, age, gender, and experience) on these intentions.

Methods: Data from 839 US residents who reported having used at least one smartphone fitness app were collected via a web-based survey. A confirmatory factor analysis was performed, and path modeling was used to test the hypotheses and explore the influence of moderators on structural relationships.

Results: The determinants explain 76% of the variance in the behavioral intention to use fitness apps. Habit (β=.42; *P*<.001), performance expectancy (β=.36; *P*<.001), facilitating conditions (β=.15; *P*<.001), price value (β=.13; *P*<.001), and effort expectancy (β=.09; *P*=.04) were positively related to behavioral intention to use fitness apps, whereas social influence and hedonic motivation were nonsignificant predictors. Behavioral intentions to use fitness apps were positively related to intentions of being physically active (β=.12; *P*<.001; R^2=0.02). Education-related app features moderated the association between performance expectancy and habit and app usage intentions; motivation-related features moderated the association of performance expectancy, facilitating conditions, and habit with usage intentions; and gamification-related features moderated the association between hedonic motivation and usage intentions. Age moderated the association between effort expectancy and usage intentions, and gender moderated the association between performance expectancy and habit and usage intentions. User experience was a nonsignificant moderator. Follow-up tests were used to describe the nature of significant interaction effects.

Conclusions: This study identifies the drivers of the use of fitness apps. Smartphone app features should be designed to increase the likelihood of app usage, and hence physical activity, by supporting users in achieving their goals and facilitating habit formation. Target group–specific preferences for education-, motivation-, and gamification-related app features, as well as age and gender differences, should be considered. Performance expectancy had a high predictive power for intended usage for male (vs female) users who appreciated motivation-related features. Thus, apps targeting these user groups should focus on goal achievement–related features (eg, goal setting and monitoring). Future research could examine the mechanisms of these moderation effects and their long-term influence on physical activity.

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KEYWORDS

smartphone; fitness applications; mHealth; technology acceptance; Unified Theory of Acceptance and Use of Technology 2; physical activity; determinants of app usage; education-related app features; motivation-related app features; gamification-related app features; mobile phone

Introduction

Background

To date, there are 3.8 billion smartphone users worldwide [1], and approximately half of them consider their smartphones as something "they could not live without" [2]. Numerous smartphone apps have been developed to allow users to go beyond basic voice calling and texting to social media, gaming, and managing their health and fitness. In June 2021, 98,406 apps in the Google Play Store and 159,758 apps in the Apple App Store were available to users in the health and fitness category [3,4]. These apps aim to promote physical activity and healthy lifestyles [5,6]. It is important to increase our understanding of the factors that influence users in adopting these apps and subsequent associations with intentions to engage in healthy behaviors—both from the perspective of public health and management (eg, app providers)—because stakeholders in these domains are (or should be) interested in finding ways to promote healthy lifestyles via digitization in general and the use of mobile devices in particular.

The most widely used theoretical frameworks that explain why users adopt or use technology are the technology acceptance model [7] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [8]. The two models focus on the organizational context. In consumer settings, the second version of the UTAUT (ie, UTAUT2) has been developed to explain the acceptance of new technology by individuals [9]. Since the first application of UTAUT2 (studying the acceptance of the mobile internet), it has been used to explain smartphone app adoption and usage [10,11], among other applications. With regard to previous empirical studies on mobile health and fitness apps, important gaps exist in the research. First, previous studies have left out the essential determinants that UTAUT2 incorporates (eg, habit and hedonic motivation). Given the importance of habit [12] and hedonic motivation [13], the sole focus on the four determinants proposed by UTAUT seems insufficient [14,15]. Second, the relationship between the intentions to use fitness apps and to be physically active has not been explored. Assessing the downstream effects of intention to use fitness apps is important, because downloaded but unused apps or apps that are unable to motivate people to become or remain physically active will have fewer health benefits [5,16]. Third, understanding whether different fitness app features moderate the relationships of the UTAUT2 determinants and the behavioral intentions of using the app is lacking. Previous research has categorized app features, such as education-related versus motivation-related features [17], but did not consider their influence on structural relationships that aim to explain app usage intentions and physical activity intentions. Finally, despite the fact that the moderating effects of individual-difference variables (eg, age, gender, and experience) have been theorized and empirically assessed [9], they have largely been neglected in prior research on mobile health and fitness apps [18-21]. However, their relevance was shown in a post hoc meta-analysis, for example, in which age was a significant moderator [22].

This study aims to partially fill these gaps and answer four research questions: (1) What are the relationships between the UTAUT2 determinants and behavioral intentions of individuals to use fitness apps? (2) What is the downstream relationship between the behavioral intentions of using fitness apps and being physically active? (3) Do fitness app features moderate the relationships between the UTAUT2 determinants and the intentions of using fitness apps? (4) Are there individual differences regarding age, gender, and user experience in the relationships between the UTAUT2 determinants and intentions to use fitness apps?

To answer the research questions, we applied and extended the UTAUT2 model in the context of smartphone fitness apps. A sample of 839 individuals was surveyed to test our hypotheses. Path modeling was used to test the hypotheses. In the following, we reviewed the extant literature on determinants of fitness app usage, developed the hypotheses, and presented the methodology of our approach.

Literature Review

Smartphone Fitness Apps

Along with the growing consensus on the health benefits of physical activity [23], a myriad of fitness wearables and smartphone fitness apps have been developed to quantify and promote physical activity. Fitness wearables are "devices that offer training plans, assist with activity tracking, and generally collect and process health-related data" [24], whereas fitness apps refer to "the self-contained programs for smartphones designed for the purpose of getting fit" [25]. This study focused on smartphone fitness apps.

Despite the potential of smartphone fitness apps to deliver cost-effective physical activity and health promotion, their effectiveness has not been sufficiently established [5,16,26,27]. In particular, the effectiveness of fitness apps usage or app-based interventions was modest or short-lived [5,16]. In previous studies, only a limited number of factors considered by researchers have been based on theories or behavior change techniques [16,26,27]. Furthermore, only a small number of fitness apps have undergone rigorous evidence-based evaluations in controlled trials [28]. There are some quality concerns in the reporting of these studies, for example, only a few studies have reported whether fitness apps are based on human behavior change theories [28,29]. Herein, we outline the factors that might predict the behavioral intentions of individuals to use fitness apps (and their downstream effects), building upon theories that have been identified as relevant in the information systems literature, particularly UTAUT2.

Determinants of the Behavioral Intentions of Using Fitness Apps

Venkatesh et al [8] developed the UTAUT by integrating eight theories (ie, technology acceptance model, theory of reasoned action, motivational model, theory of planned behavior, combined technology acceptance model, theory of planned behavior model, model of PC utilization, diffusion of innovation theory, and social cognitive theory). According to UTAUT, performance expectancy, effort expectancy, social influence, and facilitating conditions are the four key determinants of behavioral intentions to use technology. In 2012, three additional factors were identified as part of the UTAUT2, namely hedonic motivation, price value, and habit [9]. In the UTAUT2, the individual-difference factors of age, gender, and experience have been identified as important moderators of the relationships between the seven determinants and behavioral intentions. Hew et al [20] applied the UTAUT2 to examine the factors that affect smartphone app adoption in general, considering the moderators of gender and education. They found that all but two factors (ie, social influence and price value) were significant determinants, with habit exerting the strongest influence. Gender and education were nonsignificant moderators. Most important to this research, previous studies used the UTAUT2 to investigate the determinants of behavioral intentions of using fitness-promoting smartwatches [18] and fitness apps [19,30]. However, none of them considered individual-difference factors as moderators, and none of them considered the effect of app features on the proposed relationships.

Specifically, Beh et al [18] found positive relationships among performance expectancy, effort expectancy, facilitating conditions, and hedonic motivation and behavioral intention to use smartwatches for fitness and health monitoring purposes. The authors postulated that perceived vulnerability to developing chronic diseases and perceived severity of chronic diseases would moderate the effects but found only weak support for their hypotheses. Dhiman et al [19] found that effort expectancy, social influence, price value, and habit were positively related to fitness app adoption intentions. They considered self-efficacy to be a predictor of effort expectancy and innovativeness as a predictor of habit; both relationships were significant. Yuan et al [30] did not consider any mediators and found that performance expectancy, hedonic motivation, price value, and habit were predictors of behavioral intentions to continuously use health and fitness apps; however, effort expectancy, social influence, and facilitating conditions were nonsignificant predictors. These studies have important limitations. First, the downstream effects on intentions of being physically active were not assessed in any of the studies. The linkage of fitness app usage intentions and intentions of being physically active is important, because health benefits can only be realized if intended app usage motivates people to become or remain physically active. Second, none of the studies considered app features to be relevant moderators, despite the fact that previous research showed that app features, such as gamification, might moderate the effects of UTAUT2 determinants on app usage intentions [31], and despite the fact that the consideration of risk perception factors (instead of app features) was largely unsuccessful [18]. Third, only one study assessed the moderating roles of age, gender, and experience. However, the authors did not include these variables in the model because of nonsignificant findings [30]. Thus, important similarities with, and differences to the original UTAUT2 studies regarding the influence of age, gender, and experience remain largely unknown. This study aims to fill these gaps partly.

Building upon UTAUT2, we first propose that the seven UTAUT2 determinants relate positively to individuals' intentions to use fitness apps. Second, we postulate positive downstream relationships with the intention of being physically active. Third, we pose a research question that considers three prominent app features (ie, education, motivation, and gamification related) as moderators of the relationships between the seven UTAUT2 determinants and behavioral intentions of using the app. Finally, we explore the moderating effects of individual differences (ie, age, gender, and experience) on the relationship between the seven UTAUT2 determinants and behavioral intentions to use the app. We have listed the hypotheses in the following sections.

Hypotheses Development

Performance Expectancy

Performance expectancy is defined as the "degree to which using a technology will provide benefits to consumers in performing certain activities" [9]. It was the strongest predictor of behavioral intentions in the original UTAUT study [8] and is a pivotal determinant of new technology acceptance in health care [32,33] and fitness wearables [21,34]. In the context of this study, performance expectancy refers to the degree to which a user believes that using a particular fitness app would help improve their fitness. Previous studies have shown a positive relationship between performance expectancy and intention to use fitness apps [15,30]. As the perception that fitness apps help people reach their fitness-related goals should be of high relevance to users, we propose the following:

Hypothesis 1: performance expectancy is positively related to individuals' behavioral intentions to use fitness apps.

Effort Expectancy

Effort expectancy refers to "the degree of ease associated with consumers' use of technology" [9], similar to the perceived ease of use as described in the technology acceptance model [7]. In this study, effort expectancy assesses the perceived ease of use of fitness apps. The easier the individuals believe the fitness apps are to use, the higher is their intention to use them. Prior studies have revealed a positive relationship between effort expectancy and behavioral intention to use fitness apps [15,19] and fitness wearables [18,34]. As people should be interested in intuitive and easy app usage, we expect the following:

Hypothesis 2: effort expectancy is positively related to behavioral intentions of individuals to use fitness apps.

Social Influence

Social influence is defined as "the extent to which consumers perceive that important others (eg, friends, peers) believe they should use a particular technology" [9]. Social influence plays a particular role when users lack information about their usage

[35]. In the context of fitness apps, previous studies have revealed inconsistent results regarding the effect of social influence on behavioral intentions of using fitness apps. It was a positive predictor of usage intentions of students of a Chinese university [15] and Indian users [19], although it did not predict the intentions of college-aged US residents [30]. Given the positive effect of social influence postulated in the original UTAUT2 [9] and the importance of social support in being physically active [36,37], we assume the following:

Hypothesis 3: social influence is positively related to the behavioral intention of individuals to use fitness apps.

Facilitating Conditions

Facilitating conditions refer to “consumers’ perceptions of the resources and support available to perform a behavior” [9]. In the context of this research, it reflects the support from resources (eg, ubiquitous internet connection for smartphones) and the required knowledge (eg, experience of smartphone use) to be able to use fitness apps. The original UTAUT2 study [9], as well as studies considering the acceptance of general apps [20] and fitness wearables [18], showed that facilitating conditions increase acceptance. Thus, we postulate the following:

Hypothesis 4: facilitating conditions relate positively to behavioral intentions of individuals to use fitness apps.

Price Value

Price value is defined as “consumers’ cognitive trade-off between the perceived benefits of a technology and the monetary cost of using it” [9]. Individuals expect a higher quality of services when they have to pay more for them [30,38]. In the fitness app context, providers offer three main patterns of pricing: free, paid, or freemium (ie, free base app use but additional features need to be paid for). Even if an app can be used for free, individuals might nevertheless consider other cost aspects, such as personal time costs or psychological costs. Previous studies have found a positive relationship between price value considerations and behavioral intentions to use the mobile internet [9], health care wearables [39], and fitness apps [19,30]. Owing to the fact that a high value for a given price can be assumed to be perceived positively by individuals, we propose the following:

Hypothesis 5: price value relates positively to behavioral intentions of individuals to use fitness apps.

Hedonic Motivation

Hedonic motivation refers to “the fun or pleasure derived from using a technology” [9]. If the intrinsic motivation of an individual is high, they typically have high levels of hedonic motivation [40]. A meta-analysis revealed that 58% (53/91) of the included UTAUT2-related empirical studies included hedonic motivation as a factor, whereas 81% (43/53) of the studies found a positive relationship between hedonic motivation and behavioral intentions to use the technology [13]. Hedonic motivation has a positive effect on the intention to adopt health care wearables [18,21] and fitness apps [30]. Thus, we suggest that if a user has fun using a fitness app, they are more likely to use it. Hypothesis 6 is as follows:

Hypothesis 6: hedonic motivation is positively related to the behavioral intentions of individuals to use fitness apps.

Habit

Habit refers to “the extent to which people tend to perform behavior automatically” and was found to be a positive predictor of behavioral intentions to use the mobile internet [9]. Approximately 35% (23/66) of UTAUT2-related empirical studies utilized habit as a construct [12]. Most importantly, 83% (15/18) of the studies revealed positive associations between habit and intention [12]. In the context of this study, we consider habit to be an important predictor, because smartphones are a central means by which individuals can manage and facilitate their daily lives [2] and because individuals use their smartphone (and potentially fitness apps [19,30]) by habit. We thus propose the following:

Hypothesis 7: habit relates positively with the behavioral intentions of individuals using fitness apps.

Downstream Consequence of Behavioral Intentions of Using Fitness Apps

Fitness apps aim to promote user fitness levels. As it is assumable that people who download these apps are (at least partly) committed to reaching this goal, we postulate that higher intentions to use fitness apps relate positively to the willingness of people to be physically active in the future. The claim can be substantiated by consistency theories, arguing that cognitive consistency fosters updates on the expectancy regarding an outcome or a state (here, to be physically active) [41]. However, to date none of the UTAUT2-based studies have examined the relationship between usage intentions of new technology that aims to promote fitness (or health) and the downstream consequence on behavioral intentions to engage in physical activity–related behaviors. Two recent systematic reviews concluded that the effects of fitness apps on physical activity levels are present but are modest in magnitude [5,16]. Previously formed intentions at the individual level might be explanatory variables for these effects. Thus, hypothesis 8 is stated as follows:

Hypothesis 8: behavioral intentions to use fitness apps relate positively to behavioral intentions of being physically active.

Moderating Effects of Fitness App Features

Smartphone apps have certain features, that is, the set of operational functions that an app can perform (eg, gaming). The essence of fitness app features may be summarized within behavior change techniques (eg, goal setting, monitoring, and acquisition of knowledge) [42]. In addition, various frameworks of features implemented in fitness apps have been proposed. For example, Mollee et al [43] identified user input, textual or numerical overviews, social sharing, and general instructions as the most implemented features of fitness apps. Rabin and Bock [44] suggested that fitness tracking, tracking of progress toward fitness goals, and the integration of features that increase enjoyment (eg, music) are user-desired features. Other studies focused on the social features of fitness apps (eg, sharing or comparing steps and receiving social support) [45], whereas a review concluded that the evidence of social app features to promote fitness was limited [36].

Conroy et al [17] used an empirical approach to cluster fitness apps in terms of features and used cluster analysis to identify two broad categories, namely, motivation related and education related. Motivation-related app features emphasize the social and self-regulation of fitness (eg, tracking, feedback, social support, goal setting, and reward features). Education-related app features focus on fitness education (eg, instruction, coaching, and learning) [17]. These two clusters do not include gamification-related features, which have become relevant in helping individuals improve their health and fitness [46]. Gamification-related features use game design elements to make the user experience playful and enjoyable [47,48]. In this study, we thus consider gamification-related features besides the motivation- and education-related features of fitness apps.

The literature on apps in general (without a focus on physical activity) has considered app features as moderators of the relationship between acceptance determinants and behavioral intentions of using apps [31,48]. However, it remains unclear whether the UTAUT2 determinants interact with fitness app features to explain the behavioral intentions of using these apps. Such interaction effects might explain the modest effects found in systematic reviews on the effects of fitness apps on physical activity [5,16]. To explore this issue, we formulate the following research question: do fitness app features moderate the relationships between the UTAUT2 determinants and behavioral intentions of using fitness apps?

Moderating Effects of Individual Differences

The moderating effects of age, gender, and experience—individual-difference variables—on the relationships between UTAUT2 determinants and behavioral intentions have been proposed and empirically tested in the original UTAUT2 study [9]. In particular, it was theorized that age moderated the relationships between the seven UTAUT2 determinants and behavioral intentions such that the effects are stronger among young (vs old) users for performance expectancy, effort expectancy, and hedonic motivation but weaker for social influence, facilitating conditions, price value, and habit [8,9]. Gender was postulated to moderate the relationship between the seven UTAUT2 determinants and behavioral intentions such that the effects are stronger among women (vs men) for effort expectancy, social influence, facilitating conditions, and price value but weaker for performance expectancy, hedonic motivation, and habit [8,9]. Experience was postulated to moderate the relationships between five UTAUT2 determinants and behavioral intentions such that the effects are stronger among users in the early (vs late) stage of experience for effort expectancy, social influence, facilitating conditions, and hedonic motivation but weaker for habit [8,9]. Three- and four-way interactions of age, gender, and experience were included in the original UTAUT2 study [9]. Despite the fact that the original studies supported these proposed moderator relationships, previous studies on mobile health and fitness apps applying the UTAUT or UTAUT2 did not fully consider them [14,15,18-21,49]. The moderators have been meta-analyzed and suggested as worthy of study [22] or noted as future work [19].

To fill this research gap, we state the following research question: are there individual differences in the relationships between the UTAUT2 determinants and intentions to use fitness apps?

Methods

Study Design and Procedure

This study applied a cross-sectional web-based survey design, and the results were reported according to the CHERRIES checklist [50]. Using a convenience sampling technique, we recruited 867 Amazon Mechanical Turk workers in March 2020. This sample size was considered sufficient based on a thumb rule [51], as well as similar studies on fitness app acceptance [19,30]. Participants were limited to healthy adults who were aged between 18 and 65 years, owned a smartphone, and had downloaded at least one smartphone fitness app. Participants were also required to be able to read and understand English and be located in the United States (ie, US residents). Participants who met the eligibility criteria were invited to participate in the Amazon Mechanical Turk online survey, delivered via Qualtrics. All participants were informed about the study procedures via detailed instructions at the beginning of the survey (Multimedia Appendix 1), including the purpose, inclusion criteria, and estimated time needed to complete the survey. After the instructions were provided, informed consent was obtained from each participant. The survey consisted of UTAUT2-related questions, questions that assessed the dependent variables as well as mediators and moderators, and demographics of participants, which were collected at the end of the survey. Each participant was compensated with US $1.50 for their participation. Once 28 incomplete surveys were eliminated, data from 839 respondents were retained for analysis.

This study was conducted in accordance with the ethical standards of the university faculty board, which acts as the local ethics committee for studies outside the Faculty of Medicine, and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Measures

The UTAUT2 items for the seven determinants and behavioral intentions of using apps were adapted to the context of this study [9]. They were measured on a 7-point rating scale ranging from 1 (strongly disagree) to 7 (strongly agree). The behavioral intentions of being physically active were gauged using two separate measures. First, intentions were measured via an adaptation of the International Physical Activity Questionnaire Short Form [52], which covers a period of 4 weeks in the future. The sum of the values (measured in metabolic equivalent of task [MET] min/week) was calculated according to established data processing guidelines [53]. Second, it was measured using a single question: "To what degree do you want to be physically active in the next four weeks?" (1=not at all; 7=very much) [54]. The individual-difference variables of age and gender were self-reported. Experience was measured with a single item: "When did you download a fitness app for the first time? - () months ago," as done in the original UTAUT2 study [9].

Participants also rated the features of their most preferred app with importance ratings (1=not important at all; 7=extremely important). Importance ratings were used because apps typically have multiple features and because the features from the perspective of users are important in this study [55]. The items for education- and motivation-related app features were formulated in agreement with previous cluster classifications [17] and substantive content of behavior change techniques [42]. Gamification-related app features were operationalized based on the extant literature on gamification and fitness apps [47,56]. All three app features were measured using three items each. Examples of items are as follows: "How important to you are app features that motivate you to be physically active?" for motivation-related features; "How important to you are app features that educate yourself about how to exercise best?" for education-related features; and "How important to you are app features to enjoy yourself while exercising?" for gamification-related features.

Statistical Analyses

Normality was evaluated using multivariate skewness and kurtosis [57]. We conducted a confirmatory factor analysis to evaluate the internal reliability, convergent validity, and discriminant validity of the measurement model [58]. For internal reliability, we examined the Cronbach α (>.70) and construct reliability (>0.70). We used the average variance extracted (AVE; AVE>0.50) and factor loadings for convergent validity [59]. Discriminant validity was assessed using the Fornell-Larcker criterion [59] and the heterotrait-monotrait (HTMT) criteria [60]. Various model fit indices were applied, including the normed chi-square statistic (χ^2/df ratio, value<3.0), Tucker-Lewis index (TLI; TLI>0.90), comparative fit index (CFI; CFI>0.90), root mean square error of approximation (RMSEA; RMSEA<0.05), and standardized root mean square residual (SRMR; SRMR<0.05) [58].

Path modeling (maximum likelihood) was used to test the hypotheses. The variables were mean-centered before the analysis, and gender was coded as a dummy variable (0=female; 1=male). For significant interaction effects between the UTAUT2 determinants and app features, follow-up tests were performed to observe how the moderator changes the hypothesized relationships, as recommended by Dawson [61]. Data analyses were performed using R (RStudio) and the *lavaan* package [62]. The level of significance was set at $P<.05$.

Participants

A total of 839 participants completed the study. The participants were from 49 US states, with a median of 10 participants per state. They were aged, on average, 37 (SD 10.2) years; 48.3% (405/839) were female; and 51.7% (434/839) were male. Participants were experienced in using fitness apps, as on average they had downloaded the app about 30 months ago. Most participants were White (681/839, 81.2%), employed workers (676/839, 80.6%), married (442/839, 52.7%), and single (322/839, 38.4%). About 66.7% (560/839) reported having a bachelor's degree or higher, whereas 33.3% (279/839) held an associate's degree or lower. They were mostly young adults (562/839, 67% aged between 18 and 40 years), and approximately 44.8% (376/839) of them were either overweight or obese. Approximately 76% (638/839) of them had downloaded two or more fitness apps (mean 3.4, SD 2.5). When asked about their preferred fitness app, 14.1% (118/839) stated MyFitnessPal, 13.2% (111/839) stated Fitbit, and 6.2% (52/839) stated Samsung Health (which are among the preferred apps in real-time app rankings under the category of health and fitness in both the Apple App Store and Google Play Store). In total, 159 different apps were mentioned as the preferred apps by the participants. Table 1 shows the sociodemographic characteristics of the participants.

Table 1. Sociodemographic characteristics of participants (N=839).

Variables	Values
Age (years), mean (SD)	37.3 (10.2)
Gender (female), n (%)	405 (48.3)
BMI[a] (kg/m^2)	
Value, mean (SD)	25.3 (6)
Underweight, n (%)	63 (7.5)
Normal, n (%)	400 (47.7)
Overweight, n (%)	237 (28.3)
Obese, n (%)	139 (16.6)
Education levels, n (%)	
High school degree or below	130 (15.5)
Associate degree	149 (17.8)
College bachelor’s degree	390 (46.5)
Master’s degree	153 (18.2)
PhD	17 (2)
Marital status, n (%)	
Single (never married)	322 (38.4)
Married	442 (52.7)
Divorced	69 (8.2)
Widowed	6 (0.7)
Income (US $; gross per year), n (%)	
≤15,000	89 (10.6)
15,000-24,999	66 (7.9)
25,000-34,999	104 (12.4)
35,000-49,999	189 (22.5)
50,000-64,999	132 (15.7)
65,000-79,999	122 (14.5)
≥80,000	137 (16.3)
Employment, n (%)	
Employed	676 (80.6)
Self-employed	101 (12)
Unemployed	62 (7.4)
Ethnicity, n (%)	
White	681 (81.1)
Black or African American	84 (10)
Asian	46 (5.5)
Other	28 (3.3)

[a]BMI was classified according to the US Centers for Disease Control and Prevention’s BMI weight status categories: underweight (below 18.5 kg/m^2); normal or healthy weight (18.5 to 24.9 kg/m^2); overweight (25.0 to 29.9 kg/m^2); and obese (over 30.0 kg/m^2).

Results

Descriptive Statistics and Assumption Tests

Table 2 provides an overview of the descriptive statistics of the variables. The average ratings of the UTAUT2 determinants ranged from 4.26, for social influence, to 6.02, for facilitating conditions. Education-, motivation-, and gamification-related app features were considered important, with the highest ratings for motivation (mean 5.21) compared with gamification- and education-related app features (mean 5 for both). Participant ratings of their behavioral intentions to use fitness apps were above the midpoint of the scale (mean 5.53); intentions of being physically active in the future were very high for both MET values and the ratings on the seven-point rating scale (mean 4589 MET min/week, SD 3137; and mean 6.07, SD 1.05, respectively). All values of skewness and kurtosis were within the suggested criteria (ie, skewness <2 and kurtosis <7 [63]), indicating normality of the univariate distribution.

Table 2. Measurement model: descriptive statistics, reliability, and convergent validity.

Constructs[a] and items	Value, mean (SD)	Skewness[b]	Kurtosis[b]	Reliability		Convergent validity	
				Cronbach α	Composite reliability	Factor loadings	AVE[c]
Performance expectancy				.87	0.87		0.70
I find the [xx][d] app useful in my daily life	5.54 (1.41)	–1.07	0.88			0.84	
Using the [xx] app helps me accomplish things	5.43 (1.38)	–1.02	0.98			0.86	
Using the [xx] app increases my physical activity levels	5.50 (1.35)	–1.05	1.08			0.80	
Effort expectancy				.89	0.89		0.68
Learning how to use the [xx] app is easy to me	6.02 (1.11)	–1.41	2.52			0.84	
My interaction with the [xx] app is clear and understandable	6.01 (1.09)	–1.4	2.62			0.84	
I find the [xx] app easy to use	6.05 (1.09)	–1.48	2.64			0.86	
It is easy for me to become skillful at using the [xx] app	5.90 (1.12)	–1.27	2.13			0.77	
Social influence				.94	0.94		0.83
People who are important to me think that I should use the [xx] app	4.30 (1.70)	–0.26	–0.56			0.87	
People who influence my behavior think that I should use the [xx] app	4.24 (1.73)	–0.25	–0.64			0.92	
People whose opinions that I value prefer that I use the [xx] app	4.23 (1.72)	–0.29	–0.60			0.94	
Facilitating conditions				.77	0.78		0.54
I have the resources necessary to use the [xx] app	6.08 (1.11)	–1.54	3.03			0.83	
I have the knowledge necessary to use the [xx] app	6.18 (1.05)	–1.53	2.87			0.83	
The [xx] app is compatible with other technologies I use	5.80 (1.29)	–1.24	1.61			0.57	
Hedonic motivation				.91	0.91		0.78
Using the [xx] app is fun	5.07 (1.42)	–0.66	0.27			0.93	
Using the [xx] app is enjoyable	5.24 (1.40)	–0.80	0.50			0.91	
Using the [xx] app is very entertaining	4.71 (1.58)	–0.48	–0.32			0.82	
Price value				.90	0.91		0.76
The [xx] app is reasonably priced	6.28 (1.13)	–1.7	2.59			0.81	
The [xx] app is a good value for the money	6.21 (1.14)	–1.5	1.85			0.93	
At the current price, the [xx] app provides a good value	5.23 (1.15)	–1.72	2.98			0.88	
Habit				.80	0.84		0.66
The use of the [xx] app has become a habit to me	5.34 (1.67)	–1.04	0.33			0.54	
I am addicted to using the [xx] app	3.65 (1.96)	0.09	–1.25			0.87	
I must use the [xx] app	3.84 (1.98)	–0.05	–1.24			0.90	

Constructs[a] and items	Value, mean (SD)	Skewness[b]	Kurtosis[b]	Reliability		Convergent validity	
				Cronbach α	Composite reliability	Factor loadings	AVE[c]
BI[e]				.89	0.89		0.73
I intend to continue using the [xx] app in the future	5.77 (1.37)	–1.41	2.02			0.83	
I will always try to use the [xx] app in my daily life	5.22 (1.55)	–0.92	0.37			0.85	
I plan to continue to use the [xx] app frequently	5.61 (1.45)	–1.27	1.46			0.89	
MO[f]				.85	0.85		0.65
How important to you are app features that motivate you to be physically active?	5.13 (1.54)	–0.88	0.31			0.83	
How important are app features that help you to increase your physical activity levels?	5.38 (1.42)	–1.04	0.88			0.82	
How important to you are app features that remind you to be physically active?	5.11 (1.63)	–0.87	0.17			0.77	
ED[g]				.90	0.90		0.74
How important to you are app features that educate yourself about how to exercise best?	5.01 (1.62)	–0.77	–0.11			0.86	
How important to you are app features that tell you how things work when exercising?	4.87 (1.61)	–0.66	–0.30			0.85	
How important to you are app features that help you do the right things when exercising?	5.11 (1.58)	–0.81	0.12			0.87	
GA[h]				.84	0.84		0.63
How important to you are app features to enjoy yourself while exercising?	5.20 (1.55)	–0.88	0.30			0.86	
How important to you are app features that gamify the exercise experience?	4.62 (1.83)	–0.51	–0.74			0.68	
How important to you are app features that make the exercise experience joyful?	5.16 (1.52)	–0.93	0.47			0.88	
PA[i]				N/A[j]	N/A		N/A
Intentions of being physically active during the next 4 weeks (MET[k] min/week)	4589 (3137)	1.13	1.66			1	
Intentions of being physically active during the next 4 weeks (1-7 rating scale)	6.07 (1.05)	–1.17	1.68			1	
EXP[l]							

Constructs[a] and items	Value, mean (SD)	Skewness[b]	Kurtosis[b]	Reliability		Convergent validity	
				Cronbach α	Composite reliability	Factor loadings	AVE[c]
When did you download a fitness app for the first time? (months ago)	30.07 (25.76)	1.39	2.62	N/A	N/A	1	N/A

[a]Model fit was satisfactory: χ^2_{564}=2112.2; χ^2/df=3.8; comparative fit index=0.93; Tucker-Lewis index=0.91; root mean square error of approximation=0.06; and standardized root mean square residual=0.07.

[b]The criteria for skewness (absolute value <2) and kurtosis (absolute value <7) were fulfilled for a sample size greater than 300 (ie, N=839), indicating normality of the univariate distribution [63].

[c]AVE: average variance extracted.

[d][xx] refers to the brand name of the specified fitness app.

[e]BI: behavioral intentions to use the fitness app.

[f]MO: motivation-related app features.

[g]ED: education-related app features.

[h]GA: gamification-related app features.

[i]PA: Intentions of being physically active. The intentions were measured using the International Physical Activity Questionnaire (metabolic equivalent of task min/week) and a single-item 7-point rating scale. The reported measurement model is based on the first measure.

[j]N/A: not applicable.

[k]MET: metabolic equivalent of task.

[l]EXP: user experience with fitness apps.

Measurement Model

The overall model fit using MET minutes per week values for physical activity intentions as the dependent variable was found to be satisfactory (χ^2_{564}=2112.2; χ^2/df=3.8; CFI=0.93; TLI=0.91; RMSEA=0.06; and SRMR=0.07), after excluding one item for facilitating conditions (ie, “I can get help from others when I have difficulties using the [*brand name*] app” with a factor loading of 0.30). The internal reliability, convergent validity, and discriminant validity of the measurement model were evaluated. All Cronbach α and construct reliability values were ≥.77 (ie, above the suggested threshold of 0.70), indicating internal reliability. The AVE and factor loadings were >0.54, in all cases, above the thresholds of 0.50, suggesting convergent validity (Table 2).

Table 3 shows the results of the discriminant validity. First, no cross-loadings were detected among the measurement items. Second, all the square roots of AVE were greater than the relevant interconstruct correlations with two exceptions (ie, performance expectancy: 0.88; and facilitating conditions: 0.87). The HTMT criteria were fulfilled (ie, all HTMT values were ≤0.85) with one exception (performance expectancy: 0.88), but the value is still within the acceptable range between 0.85 and 0.90 [60].

Table 3. Discriminant validity of the measurement model: Fornell-Larcker criterion and heterotrait-monotrait ratio.

Variables	BI[a]	PE[b]	EE[c]	SI[d]	FC[e]	HM[f]	PV[g]	HA[h]	MO[i]	ED[j]	GA[k]	PA[l]	Age	GEN[m]	EXP[n]
BI	*.856* [o]	.879	.646	.414	.623	.604	.473	.795	.423	.218	.241	N/A[p]	N/A	N/A	N/A
PE	.875	*.835*	.651	.464	.594	.694	.405	.747	.635	.368	.378	N/A	N/A	N/A	N/A
EE	.637	.648	*.823*	.181	.785	.435	.614	.341	.321	.147	.179	N/A	N/A	N/A	N/A
SI	.407	.455	.168	*.911*	.135	.536	.057	.616	.366	.366	.375	N/A	N/A	N/A	N/A
FC	.584	.561	.871	.090	*.733*	.394	.678	.281	.278	.146	.178	N/A	N/A	N/A	N/A
HM	.607	.693	.446	.517	.363	*.881*	.254	.650	.515	.458	.571	N/A	N/A	N/A	N/A
PV	.467	.412	.619	.046	.645	.266	*.873*	.181	.199	.077	.097	N/A	N/A	N/A	N/A
HA	.592	.569	.180	.590	.091	.536	.027	*.811*	.470	.316	.366	N/A	N/A	N/A	N/A
MO	.423	.630	.319	.356	.253	.519	.203	.404	*.806*	.683	.712	N/A	N/A	N/A	N/A
ED	.222	.365	.148	.364	.125	.451	.078	.303	.680	*.861*	.632	N/A	N/A	N/A	N/A
GA	.243	.366	.188	.346	.156	.549	.107	.339	.706	.637	*.794*	N/A	N/A	N/A	N/A
PA	.133	.130	.073	.032	.060	.176	.067	.079	.046	.104	.036	*N/A*	N/A	N/A	N/A
Age	.038	.026	.003	–.036	.053	–.034	.084	.001	.055	–.033	–.011	–.035	*N/A*	N/A	N/A
GEN	.019	.064	.118	–.092	.058	–.038	.041	–.016	.157	.063	.096	–.057	.061	*N/A*	N/A
EXP	.095	.043	.159	–.140	.196	.009	.179	–.099	–.040	–.068	–.061	.084	.051	–.011	*N/A*

[a]BI: behavioral intentions to use the fitness app.

[b]PE: performance expectancy.

[c]EE: effort expectancy.

[d]SI: social influence.

[e]FC: facilitating conditions.

[f]HM: hedonic motivation.

[g]PV: price value.

[h]HA: habit.

[i]MO: motivation-related app features.

[j]ED: education-related app features.

[k]GA: gamification-related app features.

[l]PA: intentions of being physically active.

[m]GEN: gender.

[n]EXP: user experience with fitness apps.

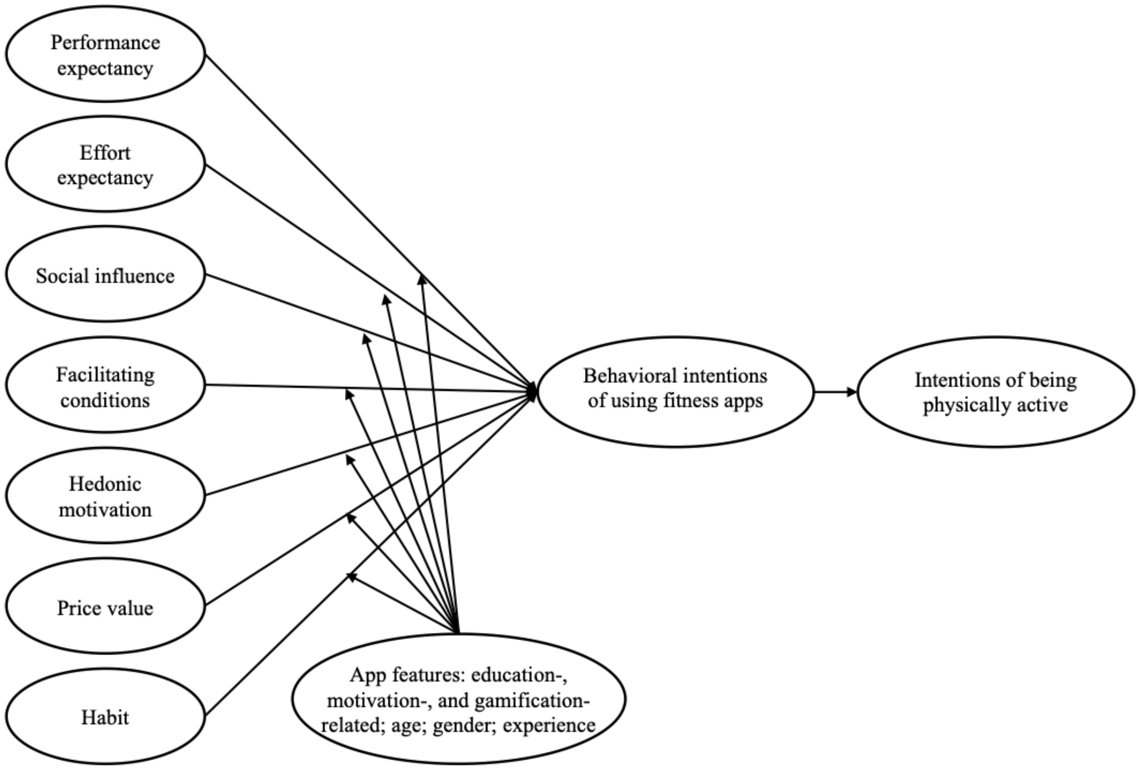
[o]Terms in italics along the diagonal are square roots of average variance extracted. Below the diagonal, the lower left metrics test the discriminant validity according to the Fornell-Larcker criterion. Discriminant validity is fulfilled if the square roots of the average variance extracted are larger than the relevant interconstruct correlations. Furthermore, above the diagonal, the upper right metrics refer to the heterotrait-monotrait ratio, where <0.85 or <0.90 indicates good discriminant validity.

[p]N/A: not applicable.

Structural Model and Hypotheses Testing

Path modeling was used to test the hypotheses. The model was established by modeling the hypothesized paths among the UTAUT2 determinants, behavioral intentions of using fitness apps, intentions of being physically active, and the three app features (Figure 1). On the basis of the different measures of intention to be physically active, two models were established. The first model (considering physical activity intentions measured in MET min/week) had an excellent fit ($\chi^2_{79.00}$=97.74; χ^2/df=1.2; *P*=.08; CFI=0.984; TLI=0.968; RMSEA=0.017; SRMR=0.006). The model fit for the second model (taking into account physical activity intentions measured on a single-item rating scale) was also good ($\chi^2_{79.00}$=179.07; χ^2/df=2.3; *P*<.001; CFI=0.925; TLI=0.849; RMSEA=0.039; SRMR=0.010). Both models explained 76% of the variance in the behavioral intentions to use fitness apps.

Figure 1. Hypothesized model for predicting behavioral intentions of using fitness apps and engaging in physical activity based on Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the consideration of app features. In agreement with the original UTAUT2 study, experience was postulated to not moderate the relationships between performance expectancy and price value and behavioral intentions of using fitness apps.



In what follows, we first present the results of model 1. Performance expectancy (β=.36, *SE* 0.04; *P*<.001), effort expectancy (β=.09, *SE* 0.04; *P*=.04), facilitating conditions (β=.15, *SE* 0.04; *P*<.001), price value (β=.13, *SE* 0.03; *P*<.001), and habit (β=.42, *SE* 0.04; *P*<.001) were positively related to behavioral intention to use fitness apps, whereas social influence (β=.03, *SE* 0.03; *P*=.37) and hedonic motivation (β=.02, *SE* 0.03; *P*=.63) were nonsignificant predictors. Behavioral intentions to use fitness apps relate positively to intentions of being physically active (β=.12, *SE* 0.03; *P*<.001), explaining 2% of the variance in physical activity intentions. For model 2, the path coefficients between the UTAUT2 determinants and behavioral intentions of using the fitness app were identical to the results obtained from model 1. Behavioral intentions to use fitness apps relate positively to intentions of being physically active (β=.37, *SE* 0.03; *P*<.001), explaining 12% of the variance in physical activity intentions. Thus, hypotheses 1, 2, 4, 6, 7, and 8 were supported, whereas hypotheses 3 and 5 were not supported (Table 4; Figure 2).

Table 4. Path coefficients and hypotheses testing for the seven UTAUT2 determinants and app-feature moderators.

Path	β[a] (*SE*)	Z value	*P* value	Hypothesis testing
UTAUT2 [b] determinants				
PE[c]→BI[d]	.36 (0.04)	8.62	<.001	Hypothesis 1 is supported
EE[e]→BI	.09 (0.04)	2.02	.04	Hypothesis 2 is supported
SI[f]→BI	.03 (0.03)	0.90	.37	Hypothesis 3 is not supported
FC[g]→BI	.15 (0.04)	3.55	<.001	Hypothesis 4 is supported
HM[h]→BI	.02 (0.03)	0.49	.63	Hypothesis 5 is not supported
PV[i]→BI	.13 (0.03)	3.97	<.001	Hypothesis 6 is supported
HA[j]→BI	.42 (0.04)	11.52	<.001	Hypothesis 7 is supported
BI→PA[k]	.12 (0.03)	3.60	<.001	Hypothesis 8 is supported
Education-related features				
ED[l]→BI	–.02 (0.03)	–0.89	.37	N/A[m]
ED×PE→BI	–.08 (0.03)	–2.46	.01	N/A
ED×EE→BI	.01 (0.04)	0.17	.86	N/A
ED×FC→BI	.06 (0.04)	1.80	.07	N/A
ED×HM→BI	–.02 (0.03)	–0.76	.45	N/A
ED×PV→BI	–.04 (0.03)	–1.17	.24	N/A
ED×SI→BI	.02 (0.03)	0.70	.48	N/A
ED×HA→BI	.08 (0.03)	2.63	.009	N/A
Motivation-related features				
MO[n]→BI	–.07 (0.03)	–2.34	.02	N/A
MO×PE→BI	.10 (0.03)	3.16	.002	N/A
MO×EE→BI	.08 (0.04)	2.07	.06	N/A
MO×FC→BI	–.11 (0.04)	–2.79	.005	N/A
MO×HM→BI	.02 (0.03)	0.69	.49	N/A
MO×PV→BI	–.03 (0.04)	–0.72	.47	N/A
MO×SI→BI	–.01 (0.03)	–0.47	.64	N/A
MO×HA→BI	–.18 (0.03)	–5.46	<.001	N/A
Gamification-related feature				
GA[o]→BI	–.01 (0.03)	–0.47	.64	N/A
GA×PE→BI	–.03 (0.03)	–0.87	.38	N/A
GA×EE→BI	–.01 (0.04)	–0.29	.77	N/A
GA×FC→BI	–.04 (0.03)	–1.06	.29	N/A
GA×HM→BI	.07 (0.03)	2.77	.006	N/A
GA×PV→BI	.02 (0.03)	0.68	.49	N/A
GA×SI→BI	.01 (0.03)	0.52	.60	N/A
GA×HA→BI	–.04 (0.03)	–1.26	.21	N/A

[a]Unstandardized path coefficient. See Table 5 for the path coefficients of the individual-difference moderators and their interaction effects.

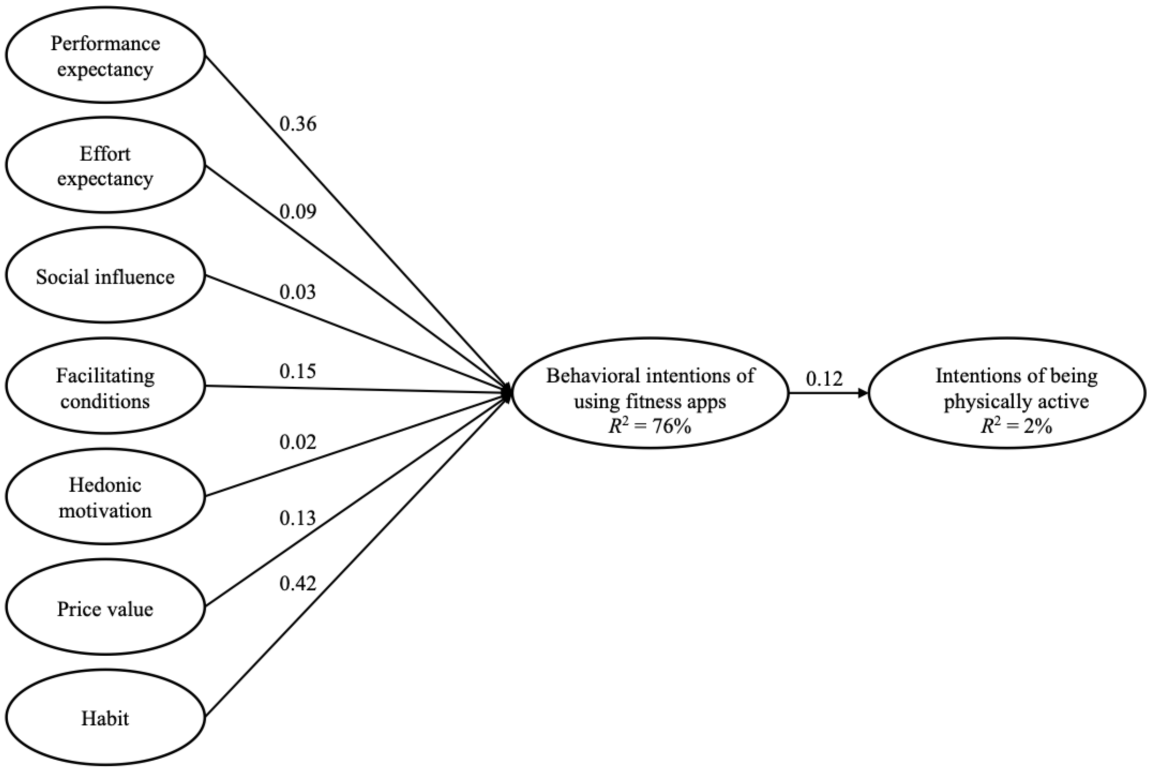
[b]UTAUT2: Unified Theory of Acceptance and Use of Technology 2.

[c]PE: performance expectancy.

[d]BI: behavioral intentions to use the fitness app.

[e]EE: effort expectancy.
[f]SI: social influence.
[g]FC: facilitating conditions.
[h]HM: hedonic motivation.
[i]PV: price value.
[j]HA: habit.
[k]PA: intentions of being physically active, measured in metabolic equivalent of task minutes per week.
[l]ED: education-related app features.
[m]N/A: not applicable.
[n]MO: motivation-related app features.
[o]GA: gamification-related app features.

Figure 2. Path modeling results on the relationship between the Unified Theory of Acceptance and Use of Technology 2 determinants and behavioral intentions of using fitness apps, as well as the downstream effects on intentions of being physically active.



The testing of the interaction effects of app features and the seven UTAUT2 determinants was performed next (Table 4). Education-related app features moderated the relationships between performance expectancy and behavioral intentions to use fitness apps (β=−.08, *SE* 0.03; *P*=.01), as well as between habit and behavioral intentions of using fitness apps (β=.08, *SE* 0.03; *P*=.009). Motivation-related app features moderated the relationships between performance expectancy and behavioral intentions of using fitness apps (β=.10, *SE* 0.03; *P*=.002), facilitating conditions and behavioral intentions to use fitness apps (β=−.11, *SE* 0.04; *P*=.005), and habit and behavioral intentions to use fitness apps (β=−.18, *SE* 0.03; *P*<.001). Gamification-related app features moderated the relationship between hedonic motivation and behavioral intention to use fitness apps (β=.07, *SE* 0.03; *P*=.006).

The testing of the interaction effects of individual differences and the seven UTAUT2 determinants (Table 5) also revealed that age moderated the relationship between effort expectancy and behavioral intention to use fitness apps (β=−.11, *SE* 0.04; *P*=.008). Gender moderated the relationships among performance expectancy and behavioral intention to use fitness apps (β=.13, *SE* 0.06; *P*=.03), habit, and behavioral intentions (β=−.12, *SE* 0.05; *P*=.02). Experience was a nonsignificant moderator. In addition, the joint moderating tests (three- and four-way effects) taking into account individual differences revealed a significant three-way interaction for age, gender, and hedonic motivation (β=−.14, *SE* 0.06; *P*=.02); a significant three-way interaction for age, experience, and effort expectancy (β=.09, *SE* 0.03; *P*=.007), and a significant three-way interaction of age, experience, and habit on behavioral intentions to use fitness apps (β=−.12, *SE* 0.04; *P*=.004). There were no significant four-way interaction effects.

Subsequently, we conducted follow-up tests to describe how the moderators changed the relationships (Table 6), considering low (−1 SD of the mean) and high (+1 SD of the mean) values of the moderators. First, when education-related features were rated as important, the relationship between performance expectancy and usage intentions was weaker compared with when this feature was rated as unimportant. Second, when education-related features were rated as important, the relationship between habit and usage intentions was stronger compared with when these features were rated as unimportant. Third, when motivation-related features were rated as important, the relationship between performance expectancy and usage intentions was stronger, the relationship between facilitating conditions and usage intentions became nonsignificant, and the relationship between habit and usage intentions was weaker compared with when these features were rated unimportant. Fourth, when gamification-related features were rated as important, the relationship between hedonic motivation and usage intentions was stronger but still nonsignificant compared with when this feature was rated unimportant. Furthermore, the relationship between effort expectancy and usage intentions was positive for younger users but nonsignificant for older users. Finally, the relationship between performance expectancy and usage intentions was stronger among males, whereas the relationship between habit and usage intentions was stronger among females.

Table 5. Path coefficients for the individual-difference moderators and their interaction effects.

Path	β[a] (*SE*)	Z value	*P* value
Age→BI[b]	.03 (0.03)	1.26	.21
Age×PE[c]→BI	.03 (0.04)	0.74	.46
Age×EE[d]→BI	–.11 (0.04)	–2.65	.008
Age×SI[e]→BI	–.04 (0.03)	–1.35	.18
Age×FC[f]→BI	.04 (0.04)	1.08	.28
Age×HM[g]→BI	.02 (0.04)	0.45	.65
Age×PV[h]→BI	.01 (0.03)	0.30	.77
Age×HA[i]→BI	.04 (0.04)	1.05	.29
GEN[j]→BI	.06 (0.04)	1.48	.14
GEN×PE→BI	.13 (0.06)	2.20	.03
GEN×EE→BI	.004 (0.06)	–0.07	.94
GEN×SI→BI	–.04 (0.05)	–0.77	.44
GEN×FC→BI	–.06 (0.06)	–1.03	.30
GEN×HM→BI	.06 (0.05)	1.22	.22
GEN×PV→BI	–.05 (0.05)	–1.01	.31
GEN×HA→BI	–.12 (0.05)	–2.34	.02
EXP[k]→BI	.01 (0.03)	0.55	.58
EXP×EE→BI	–.01 (0.04)	–0.38	.70
EXP×SI→BI	–.02 (0.03)	–0.44	.66
EXP×FC→BI	.05 (0.04)	1.15	.25
EXP×HM→BI	.02 (0.03)	0.75	.46
EXP×HA→BI	.01 (0.03)	0.30	.76
Age×GEN→BI	–.02 (0.04)	–0.55	.58
Age×GEN×PE→BI	.10 (0.06)	1.62	.10
Age×GEN×EE→BI	.04 (0.07)	0.63	.53
Age×GEN×SI→BI	.09 (0.04)	1.96	.052
Age×GEN×FC→BI	–.002 (0.06)	–0.04	.97
Age×GEN×HM→BI	–.14 (0.06)	–2.41	.02
Age×GEN×PV→BI	–.02 (0.05)	–0.32	.75
Age×GEN×HA→BI	–.06 (0.05)	–1.16	.25
EXP×GEN→BI	.06 (0.03)	1.99	.047
EXP×GEN×EE→BI	.10 (0.06)	1.72	.09
EXP×GEN×SI→BI	.06 (0.05)	1.32	.19
EXP×GEN×FC→BI	–.04 (0.06)	–0.62	.54
EXP×GEN×HM→BI	–.07 (0.05)	–1.54	.12
EXP×GEN×HA→BI	–.02 (0.05)	–0.53	.60
Age×EXP→BI	.04 (0.04)	1.10	.27
Age×EXP×EE→BI	.09 (0.03)	2.70	.007
Age×EXP×SI→BI	–.02 (0.03)	–0.45	.65
Age×EXP×FC→BI	–.07 (0.04)	–1.71	.09

Path	β[a] (*SE*)	Z value	*P* value
Age×EXP×HM→BI	.06 (0.04)	1.76	.08
Age×EXP×HA→BI	–.12 (0.04)	–2.85	.004
Age×GEN×EXP→BI	–.002 (0.04)	–0.05	.96
Age×GEN×EXP × EE→BI	–.02 (0.06)	–0.25	.80
Age×GEN×EXP×SI→BI	–.02 (0.05)	–0.41	.70
Age×GEN×EXP×FC→BI	.04 (0.07)	0.58	.56
Age×GEN×EXP×HM→BI	–.09 (0.06)	–1.47	.14
Age×GEN×EXP×HA→BI	.03 (0.05)	0.57	.57

[a]Unstandardized path coefficient. See Table 4 for the path coefficients of the seven UTAUT2 determinants and app-feature moderators.
[b]BI: behavioral intentions to use the fitness app.
[c]PE: performance expectancy.
[d]EE: effort expectancy.
[e]SI: social influence.
[f]FC: facilitating conditions.
[g]HM: hedonic motivation.
[h]PV: price value.
[i]HA: habit.
[j]GEN: gender.
[k]EXP: user experience with fitness apps.

Table 6. Slopes for the relationship of the Unified Theory of Acceptance and Use of Technology 2 determinants with behavioral intentions of using fitness apps at different values of the moderator.

Interactions	Low[a] (–1 SD of mean)			High[b] (+1 SD of mean)		
	Slope	*t* test	*P* value	Slope	*t* test	*P* value
ED[c]×PE[d]	0.36	8.05	<.001	0.28	2.56	.01
ED×HA[e]	0.42	9.39	<.001	0.50	4.56	<.001
MO[f]×PE	0.36	8.05	<.001	0.46	4.20	<.001
MO×FC[g]	0.14	3.13	.002	0.03	0.27	.78
MO×HA	0.42	9.39	<.001	0.24	2.19	.03
GA[h]×HM[i]	0.02	0.45	.66	0.09	0.82	.41
Age×EE[j]	0.09	2.01	.04	–0.02	–0.18	.86
GEN[k]×PE	0.36	8.05	<.001	0.49	4.47	<.001
GEN×HA	0.42	9.39	<.001	0.30	2.74	.006

[a]Low: low moderators.
[b]High: high moderators.
[c]ED: education-related app features.
[d]PE: performance expectancy.
[e]HA: habit.
[f]MO: motivation-related app features.
[g]FC: facilitating conditions.
[h]GA: gamification-related app features.
[i]HM: hedonic motivation.
[j]EE: effort expectancy.
[k]GEN: gender. The results for females (dummy: 0) are reported as low moderators; the results for males (dummy: 1) are reported as high moderators.

Discussion

Principal Findings

The purpose of this study was to examine the influence of the UTAUT2 determinants, as well as the moderating effects of different smartphone fitness app features (ie, education, motivation, and gamification related) and individual differences (ie, age, gender, and experience) on the app usage intentions of individuals and their behavioral intentions of being physically active. The results showed that habit and performance expectancy were the two strongest predictors of intentions of individuals to use fitness apps. The effects of performance expectancy were greater when motivation-related features were rated as important and when education-related features were rated as less important. Moreover, the effects of performance expectancy were greater for males. The effects of habit were greater when education-related features were rated as important and when motivation-related features were rated as less important. Furthermore, the effects of habit were greater for females. Age moderated the relationship between effort expectancy and app usage intention. The intentions of individuals to use fitness apps predicted their intentions of being physically active, using two different means of measuring future physical activity.

Theoretical Contribution

We contribute to the literature on mobile health and physical activity in several ways. Answering the first research question (*What are the relationships between the UTAUT2 determinants and intentions to use smartphone fitness apps?*), we found positive relationships among habit, performance expectancy, facilitating conditions, price value, effort expectancy, and behavioral intentions to use fitness apps. Habit and performance expectancy were found to be the most important predictors of intention to use fitness apps, consistent with prior studies (eg, habit [19,20,30] and performance expectancy [14,15,30]). Positive relationships have also been identified for effort expectancy [18-20], facilitating conditions [18,20,21], and price value [19,21,30].

Social influence was a nonsignificant predictor of intention [18,20,30]. Interestingly, the latter finding is not due to the high domain-specific experience of users (given the nonsignificant interaction effect of social influence and experience), who might have relied less on peer opinions for their evaluations and intentions than low-experience users. Furthermore, in contrast to the original UTAUT2 study [9] and previous studies [18,20,21,30], but in agreement with Dhiman et al [19], we found a nonsignificant relationship between hedonic motivation and app usage intentions. This may be explained by the high demands of fitness app users on app usage to achieve their physical activity goals, compared with the fun or pleasure derived from the apps. However, focusing solely on the four determinants proposed by the first version of UTAUT [14,15,34] may be insufficient. Habit, in particular, is the strongest determinant linked to the intention to use fitness apps in this study.

Answering the second research question (*What is the downstream relationship between the behavioral intentions of using fitness apps and of being physically active?*), we contribute to UTAUT2-based research by showing that app usage intentions have important downstream consequences. In particular, individuals have greater intentions of being physically active when they have higher intentions to use fitness apps. Assessing the downstream effect of intention to use fitness apps is important, because downloaded but unused apps or apps unable to motivate people to become or remain physically active will have little health effects [5,16]. The positive relationship between fitness app usage intentions and physical activity intentions indicates that app usage might motivate people to become or remain active. The findings thus contribute to previous research into whether, and when, mobile health and fitness apps may help individuals become physically active [64,65]. However, it should be noted that the intentions of individuals to be physically active are affected by numerous correlates and determinants (eg, self-efficacy, sociodemographic variables, sport club membership, among others) [66], and the intention-behavior gap is considerable [67]. Thus, adding these factors and incorporating measurements of actual physical activity may be warranted in the future.

Answering the third research question (*Do fitness apps moderate the relationships between the UTAUT2 determinants and intentions of using fitness apps?*), this study contributes to previous research that categorized app features [17] yet ignored their influence on the structural relationships proposed by the UTAUT2. On the basis of our exploratory analysis, we identified six relevant interaction effects. One of the most intuitive findings was that when motivation-related features were rated as important, the relationship between performance expectancy and intentions was strong. Research into goal achievement [68,69] might explain the interaction effect: individuals who are interested in improving their physical activity levels, or keeping them at certain levels, might use the app exactly for this purpose. Among the three features, motivational elements aim most directly to help users stick to their goals and plans [70]; as there is goal congruence, the effect is strong [71]. When motivation-related features were rated as important, the relationship between facilitating conditions and usage intentions was not significant. This makes sense, because people who lack resources and capacities are more dependent on help from others compared with people who do have these resources and capacities, particularly when motivation features are not considered crucial (ie, motivation might "not be the problem"). In addition, when motivation-related features were important, the relationship between habit and intention was weaker compared with when this feature was unimportant. This finding might indicate that when habits have been formed, features that motivate individuals to be active (eg, reminders) become less important to these app users [72].

This study also found that performance expectancy had a greater effect on usage intentions when education-related features were rated as unimportant. In this case, individuals might be less interested in being educated—an aspect that might distract them from achieving their goals. In addition, the effect of habit on usage intention was stronger when education-related features were rated as important. This may be explained by the fact that habits of individuals are formed best when they are exposed to education-related cues when using an app (eg, how and when to exercise best) [73]. Regarding the interaction between hedonic motivation and gamification-related features, no final conclusions can be drawn. Although research into intrinsic motivation [74] and flow [75] may lead us to propose that intrinsic motivation, as a principal source of enjoyment, may be enhanced by the gamification app features (eg, apps using incommensurate gamification elements [likes]) [76], the follow-up tests did not reach significant levels in this study.

Answering the fourth research question (*Are there individual differences in age, gender, and user experience between the relationships of the UTAUT2 determinants and intentions to use fitness apps?*), we found partly significant, partly nonsignificant moderating effects of age, gender, and experience. First, the relationship between effort expectancy and app usage intentions was stronger among younger individuals, which agrees with the original UTAUT2 study [8,9] and a meta-analysis (ie, age group of those aged 25 to 30 years) [22]. Second, the relationship between performance expectancy and usage intentions was stronger among males, which is consistent with the original UTAUT2 study. In contrast, the relationship between habit and usage intention was stronger among females [9]. Thus, females were not more sensitive to new cues, which might have weakened the effect of habit on behavioral intentions. In the context of fitness apps, females may indeed be prone to cues that help them form health-related habits, because they are interested in health- and body-appearance-related topics. Finally, in this study, experience was a nonsignificant moderator regarding the interaction effects of the UTAUT2 determinants on app usage intentions. Thus, differences in experiences between users might be less relevant today—a time in which smartphone users can easily add and delete new apps and in which users are technology savvy.

Managerial Implications

This study has implications for smartphone app designers and managers. First, they can be advised to focus on habit formation and performance (eg, goal setting) when designing fitness apps and tailoring them to potential users. Meeting users' expectations concerning facilitating conditions, price value, and effort expectancy will also increase the likelihood of the app being accepted. Second, practitioners should highlight certain app features that depend on user preferences. For example, motivation-related features are important drivers of app usage intentions for target group users who value performance (education-related features might be less relevant here); habit formation and facilitating conditions are less important to these individuals. Third, health professionals should consider age and gender differences among users with regard to the effects of effort expectancy (age) as well as performance expectancy and habit (gender). Finally, practitioners may also be advised to monitor whether app usage intentions have a positive correlation with intentions of, or even actual, physical activities so that immediate action can be taken when users lose track of their original goals (having already downloaded the app).

Limitations and Outlook

This study has some limitations. First, the generalizability of our findings is limited. We used a nonrepresentative sample of US residents who owned a smartphone and had previously used fitness apps. Future studies may consider inexperienced people with fitness apps to reveal the influence of UTAUT2 determinants on usage intentions at the early- or preadoption stage. Second, given this research design, we did not consider one specific fitness app, but participants stated their preferred app and rated the features of this app. Thus, we considered a variety of apps (which might be beneficial for external validity, given the myriad of apps on the market [3,4]). Researchers might collaborate with certain providers and use real-world app data and objectively measure actual physical activity to validate our findings. Third, we relied on self-reported physical activity intentions using a single measure and the International Physical Activity Questionnaire Short Form. Overreporting is common for the latter (eg, approximately 84% [77]). Finally, future research could look into the mechanisms of moderation effects on individuals' behavioral intentions to use apps, incorporate app features into mobile health interventions accordingly, and evaluate their long-term influence on physical activity levels.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Online instructions to participants.
[DOCX File , 14 KB-Multimedia Appendix 1]

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Abbreviations

AVE: average variance extracted
CFI: comparative fit index

HTMT: heterotrait-monotrait
MET: metabolic equivalent of task
RMSEA: root mean square error of approximation
SRMR: standardized root mean square residual
TLI: Tucker-Lewis index
UTAUT: Unified Theory of Acceptance and Use of Technology

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Essay 1: Electronic Appendix

Manuscript title:	Determinants of fitness app usage and moderating impacts of education-, motivation-, and gamification-related app features on physical activity intentions: Cross-sectional survey study
Authors:	Yanxiang Yang, Joerg Koenigstorfer
Journal title:	Journal of Medical Internet Research

Appendix: Online instructions provided to participants

Dear participants,

Welcome to this study conducted by the Technical University of Munich. Before you decide whether to take part or not, please take the time to read the following information.

Please only participate in the study if: (1) you own a smartphone and have downloaded an app for physical activity in the past; (2) you are between 18 and 65 years old; (3) you are healthy (namely, without any physical disabilities or chronic diseases that prevent you from being physically active); (4) you are a native English speaker.

The purpose of this study is to explore your habits in relation to smartphone fitness app use and physical activity. Physical activity refers to any bodily movements that result in energy expenditure, which includes not only exercise and sport, but also all activities undertaken while you are working, carrying out house and yard work, traveling, and engaging in recreational activities. Fitness apps for physical activity are typically offered in the Health and Fitness app category in the Google Play Store (Android) or the iOS App Store.

You will be asked to rate/choose different statements according to your feelings, behaviours, and experiences. There are no right or wrong answers. Please try to answer the questions as honest and accurate as possible.

The completion of the study will take about 20-25 minutes, and you will be compensated with $1.50 for your participation. At the end of this study, you will receive a payment onto your account by providing the MTurk payment code provided to you. You must enter this code to receive a payment.

Your participation in this research study is completely voluntary and you may exit at any time. Participation in the study does not involve any risk to you beyond that of everyday life. In addition, all responses are kept confidential and will be analyzed anonymously. Please note that this survey will be best displayed on a laptop or desktop computer. Some features may be less compatible for use on a mobile device.

If you have any questions about this study, or if you are interested in learning about the results of this research study, please contact [name of the researcher] via [email of researcher].

Essay 2

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TBM

ORIGINAL RESEARCH

Determinants of physical activity maintenance during the Covid-19 pandemic: a focus on fitness apps

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Abstract

There are various health benefits of regular physical activity (PA) and health risks of sedentariness. The Covid-19 pandemic may have decreased PA and increased sedentariness for several reasons (e.g., closure of gyms, family-related time constraints, and reduced outdoor mobility). Yet, to date, there are no longitudinal studies that examined whether the pandemic affects PA levels and what factors help people remain physically active during lockdown. This study aims to investigate changes in U.S. residents' PA during (vs. before) the Covid-19 pandemic and predictors of changes, with a focus on PA smartphone applications (apps) and their features (i.e., motivational, educational, or gamification related). The study utilized a two-wave longitudinal survey design with an online panel. Healthy adults (N = 431) from 45 U.S. states self-reported their PA levels before and during lockdown. PA app use and app feature ratings were assessed. t-tests and regression analyses were conducted. Moderate PA, vigorous PA, and PA measured in metabolic equivalent of task (MET) minutes per week decreased during lockdown (all $p < .01$). Controlling for PA before lockdown and individuals' PA intentions, PA app use was positively related to overall change in PA, measured in MET minutes per week (β = 15.68, standard error = 7.84, $p < .05$). PA decreased less with increasing app use frequency. When app features were added to the model, a buffering effect for gamification features was identified. The Covid-19-caused lockdown decreased U.S. residents' PA levels by 18.2%. The use of PA apps may help buffer the decline, and gamification-related app features may be particularly helpful in this context.

Keywords

Exercise, Smartphone, Applications, Mobile Internet

Implications

Practice: Individuals and health professionals can be recommended to use physical activity (PA) applications (apps), particularly gamification features, to promote PA during a pandemic.

Policy: Policymakers in public health can be recommended to fight decreases in PA during Covid-19 lockdown via collaboration with actors from the digital world, such as smartphone and PA app providers.

Research: The study is the first to show that app usage helps buffer the pandemic-caused decline in PA over and above baseline PA and behavioral intentions.

INTRODUCTION

Regular physical activity (PA) promotes people's health and is a protective factor for many leading noncommunicable diseases [1, 2]. The World Health Organization recommends 150 min of moderate PA or 75 min of vigorous PA per week, or 500–1,000 metabolic equivalent of task (MET) minutes per week for adults [3]. Despite the importance of PA, around 31% of adults fail to achieve sufficient PA [4]. The global outbreak of the coronavirus disease 2019 (Covid-19) may have decreased PA levels further [5].

Since Covid-19 first emerged in Wuhan (China) in 2019, it has infected more than 21.9 million people and resulted in at least 775,439 deaths worldwide [6]. In response to Covid-19, restricting regulations (e.g., stay-at-home policies; closure of gyms; reduced access to outdoor sport facilities; and home office regulations) may have forced many people to break their normal PA routines. Most importantly, they may have had fewer opportunities to remain physically active [5, 7].

To date, there is only suggestive evidence on whether PA levels have changed during Covid-19, and the determinants of potential changes are unclear. For example, Fitbit (a wearables provider) reported a statistically significant decline in average steps during the pandemic compared to the same time in 2019 [8]. Still, wearables or PA smartphone applications (apps) may have helped individuals remain active during restricting circumstances of Covid-19, such as lockdown [7]. Particularly, PA apps that do not require the adoption of new hardware have the potential to be cost-effective ways to promote PA, given that the users adhere to utilize the apps [9] (or, in the context of the Covid-19-caused lockdown, to reduce PA declines). To date, however, there is no evidence on whether PA levels have changed during Covid-19-caused lockdown; whether PA app use helps prevent declines in PA; and which app features are particularly helpful in this context. This study aims to fill this void of research and investigates the change in PA during the Covid-19-caused lockdown and the determinants for the maintenance of PA, with a focus on PA app use and the features of these apps.

Covid-19 and PA

Several viral epidemics have occurred in the past two decades, such as severe acute respiratory syndrome in 2003 [10], influenza A virus subtype H1N1 in 2009 [11], and Ebola virus in 2014 [12]. Covid-19 is unique in the sense that it spread quickly around the world and infected more people outside than inside China (i.e., the outbreak country). The USA is the leading country with regard to the number of infected people and Covid-19-attributed deaths [6].

Covid-19 forced governments around the world to limit the spread of the disease by implementing restrictions (e.g., closures of shops, schools, and manufactures; closure of borders to limit traveling; and implementation of social distancing rules). These restrictions may have led people to break their PA routines and become less physically active [5, 7]. Importantly, sustained low levels of PA and high levels of sedentariness are associated with poor physical and mental health and hold the potential to increase disease-specific and all-cause mortality risks [13].

Industry actors that analyzed people's mobility via wearables or smartphones found a significant decline in average step count during the Covid-19 pandemic (e.g., Fitbit Inc. [8] and Apple Inc. [14]). Additionally, cross-sectional studies showed reduced PA and increased sedentariness during Covid-19-caused lockdown among people of all ages in China [15], Italy [16], Canada [17], and Australia [18]. Those studies provide descriptive information on patterns of PA and the associated negative health effects. However, to the best of our knowledge, there are no longitudinal studies (with one exception, which recruited 70 out of 631 participants for a follow-up [15]) and none of the studies examined PA app use-related determinants that might have been helpful to residents to remain physically active during Covid-19-caused lockdown. In what follows, we briefly review the existing literature on PA apps and their potential to buffer the decline in PA during Covid-19-caused lockdown.

Smartphone apps and their potential to buffer the decline in PA

With the rapid development of technology, mobile health apps (e.g., smartphone PA apps) present cost-effective means to promote PA and prevent sedentariness [9]. Studies have emphasized the importance of such apps for remaining physically active during the critical period of Covid-19 [7, 19]. For instance, PA apps can be appealing to users, can be tailored to many people, and can be used in small spaces during lockdown. However, adherence to PA apps tends to be rather poor [9] and is influenced by as many as 89 factors [20]; among these, the perceived playfulness of PA apps might be particularly important [20].

To date, it remains largely unknown which app features help people remain physically active. Conroy et al. have cluster-analyzed PA apps and found two broad features: motivational and educational features [21]. Motivational app features emphasize social and self-regulation of PA (e.g., feedback, social support, and goal setting); educational app features focus on PA tutoring (e.g., instructions, coaching, and learning) [21]. Furthermore, gamification-related features are increasingly being used in PA apps to help individuals improve their health and fitness [22]. Gamification describes the use of game design elements, such as points, levels, and badges, to make the experience more playful and enjoyable [23, 24]. In the present study, we consider gamification-related features besides motivational and educational features of PA apps as factors to describe three relevant clusters of app features that might help predict the maintenance of PA.

Research questions of the present study

Three research questions guided the presented study:

(1) Do PA levels change during Covid-19-caused lockdown?
(2) Does the use of smartphone PA apps help individuals remain physically active during Covid-19-caused lockdown?
(3) Which PA app features support individuals in remaining physically active during Covid-19-caused lockdown?

METHODS

Study design and participants

This study utilized a two-wave longitudinal survey design with an online panel. The survey was delivered via Qualtrics and Amazon Mechanical Turk; the latter has been shown to be a reliable and useful platform to conduct behavioral research [25, 26]. The results were reported according to the CHERRIES statement for web-based surveys [27].

Participants were recruited online. Inclusion criteria were the following: healthy adults aged between 18 and 65 years old, who own a smartphone and have downloaded at least one PA app. Furthermore, participants were required to be U.S. residents who are able to read and understand English. All participants were informed about the study procedures and provided informed consent prior to the survey. Participation was voluntary and participants were informed about the confidentiality of personal information. The study was carried out in accordance with the World Medical Association Declaration of Helsinki.

Procedures

The first-wave (T0) data collection was conducted between March 12 and March 17, 2020, a time when no restricting regulations (e.g., stay-at-home order) were imposed at the U.S. state level. At T0, 867 respondents participated in the survey, and 839 were eligible after a quality check (e.g., after having eliminated incomplete surveys).

The second wave of the survey (T1) took place after the U.S. government and the states responded to the Covid-19 pandemic with restricting regulations to slow its progression (e.g., California first imposed a stay-at-home order on March 19 [28]; South Carolina did so on April 7; see Supplementary Table 1) and after these restrictions had been in place for at least 4 weeks. For example, T1 started on April 16 in California and on May 5 in South Carolina, both exactly 28 days after the lockdown. The average duration between T0 and T1 was 43.7 days (standard deviation = 4.7). Four hundred and fifty-nine participants filled in the survey at T1 and 431 were eligible after a quality check, which yields an attrition rate of 49%. We expected that those stringent regulations would reduce individuals' PA levels [29]. We further expected that the use of PA apps (and their features) would help prevent the potential decline in PA (see Research questions of the present study).

Measures

PA and intention to be physically active

PA was measured at both T0 and T1 with the International Physical Activity Questionnaire Short Form (IPAQ-SF) [30]. The IPAQ-SF asks about participants' types of PA and sedentary time during the last 7 days. Three types of PA (i.e., walking, moderate PA, and vigorous PA duration) were assessed and active PA (i.e., the sum of walking, moderate PA, and vigorous PA) and total MET were calculated (PA MET, MET minutes per week). PA MET was calculated by multiplying each activity by a weighting (i.e., 3.3 for walking, 4.0 for moderate PA, and 8.0 for vigorous PA [31]). Change in PA indicates the change in PA MET between Waves 2 and 1. The reliability and validity of the IPAQ-SF have been evidenced across 12 countries [30]. The data were processed following existing IPAQ-SF guidelines [32]. To measure individuals' intentions to be physically active at T0, similar items as the IPAQ-SF items (covering a time span of 4 weeks into the future) were used.

Smartphone app features

Participants were asked to name their most preferred PA app and then respond to questions about how they perceive the features of this particular app. Educational, motivational, and gamification-related app features were measured with a nine-item scale (i.e., three items each). Participants were asked to rate the importance of app features on a scale from 1 = "not at all important" to 7 = "extremely important" (e.g., "How important are app features that motivate you to be physically active to you?," for a motivational feature item; "How important are app features that educate yourself about how to exercise best to you?," for an educational feature item; and "How important are app features to enjoy yourself while exercising to you?," for a gamification-related feature item). Cronbach's alpha was .91 for educational, .84 for motivational, and .86 for gamification-related app features.

Usage of PA apps

PA app use was measured by assessing the frequency of use ("How often did you use [brand name; *participants' most preferred PA app was entered here*] during the past four weeks?") [33].

Sociodemographic information

Sociodemographic information was collected at T0. In particular, height (feet, inches; converted to meters) and weight (pounds, lbs; converted to kilograms) were collected and the body mass index (BMI, kg/m^2) was calculated. The educational level was classified as high school degree or below; associate's college degree; bachelor's degree; master's degree; or doctorate. Furthermore, information on marital status (single, married, divorced, or widow/widower), personal annual gross income (under U.S. \$15,000; \$15,000–24,999; \$25,000–34,999; \$35,000–49,999; \$50,000–64,999; \$65,000–79,999; or \$80,000 and more), employment status (employed; self-employed; or unemployed), and ethnicity (White/Caucasian; Black/African American; Asian; or Other) were collected.

Sample size consideration

We conducted an a priori power analysis using G*Power Version 3.1 [34] (*F*-tests, multiple regression with six predictors, and R^2 deviation from 0). The analysis revealed a sample size of at least N = 146 to determine a medium effect size of f^2 = .15 (alpha = .05; power = .95; noncentrality parameter = 21.90, critical F = 2.16). Allowing for an attrition rate of 50% at T1, a sample size of 292 is needed. The final sample size was N = 431 (i.e., 48% bigger than the recommended minimum sample size [to be able to include control variables in the analyses]).

Statistical analyses

Descriptive statistics were computed for sociodemographic information. Paired samples *t*-tests were used to compare the differences between T0 and T1. Three ordinary least squares linear regression analyses were performed to predict the maintenance of PA during lockdown. A first model tested the relationship between change in PA (T1−T0, dependent variable, Y in the regression equation, unit: MET minutes per week) and PA app use measured at T1 (independent variable, *X*, unit: frequency of use in the past 4 weeks), as well as PA measured at T0 and individuals' intentions to be physically active measured at T0 (further independent variables, *X*, unit: rating scale and MET minutes per week, respectively). In a second model, PA app features (i.e., motivational, educational, and gamification-related; *X*, unit: rating scales) were added to the model. In a third model, age, gender, BMI, education, income, marital status, employment, and ethnicity were added. The data were analyzed using R (RStudio, V1.2.5019, Boston, MA) and the level of significance was set at $p < .05$ (two tailed).

RESULTS

Characteristics of participants

Four hundred and thirty-one participants were included in the analysis (49% females). Participants lived in 45 states (with frequencies between 1 (Hawaii) and 37 (New York); median of 6 participants per state). They were mostly young adults (75% of the participants were aged between 21 and 45 years). About 47% of them were overweight or obese. About 69% of the participants had a college bachelor's or a higher degree and 84% were employed. Table 1 shows the characteristics of the sample.

Descriptive statistics and difference testing between waves

While self-reports of PA might be subject to overreporting [35] (this might also be true for the present study), the within-participant design allowed us to assess differences between the two waves. The changes in PA and sedentariness between the two waves are shown in Table 2. From T0 to T1, there was a significant decrease in moderate PA (−10.4 ± 51.5 min/day, $p < .01$) and vigorous PA (−8.5 ± 46.0 min/day, $p < .001$). There was no significant difference in walking (−4.5 ± 51.5 min/day, $p = .067$) and sedentary time (1.6 ± 170.1 min/day, $p = .85$). Both active PA (−23.4 ± 93.3 min/day, $p = .003$) and PA MET (−605.1 ± 2,453.5 MET min/week, $p < .001$, indicating a decline by 18.2%) decreased significantly. These results, thus, provide an answer to Research Question 1: PA decreased significantly during lockdown.

Predictors of change in PA

Change in PA MET was used as the dependent variable in the three models. The results for the regression analyses are shown in Table 3. The predictors included in Model 1 explain 37% of the variance in the change in PA MET. With regard to Research Question 2, PA app use was positively related with change in PA (β = 15.68, standard error [*SE*] = 7.84, $p = .04$) such that the more often the app was used, the more positive was the change in PA. The model controls for PA at T0 (i.e., before the lockdown) and individuals' stated PA intentions (i.e., their stated willingness to be active; if individuals are not intending to be active, it would be no surprise if PA declined during lockdown). PA at T0 was negatively

Table 1 | Sociodemographic characteristics of participants

Variables	*N* = 431
Age (years)	39.1 ± 10.6
Gender (*F*%)	211 (49.0%)
BMI (kg/m^2)	25.1 ± 5.6
Underweight	34 (7.9%)
Normal	227 (44.8%)
Overweight	136 (31.6%)
Obese	68 (15.8%)
Education levels	
High school degree or below	56 (13.0%)
Associate's degree	79 (18.3%)
College Bachelor's degree	206 (47.8%)
Master's degree	80 (18.6%)
PhD	10 (2.3%)
Marital status	
Single (never married)	168 (39.0%)
Married	227 (52.7%)
Divorced	32 (7.4%)
Widowed	4 (0.9%)
Income (gross, per year)	
Under $15,000	39 (9.1%)
$15,000–24,999	29 (6.7%)
$25,000–34,999	54 (12.5%)
$35,000–49,999	94 (21.8%)
$50,000–64,999	70 (15.2%)
$65,000–79,999	61 (14.2%)
$80,000 and above	84 (19.5%)
Employment	
Employed	362 (84.0%)
Self-employed	39 (9.1%)
Unemployed	30 (7.0%)
Ethnicity	
White/Caucasian	354 (82.1%)
Black/African American	33 (7.7%)
Asian	28 (6.5%)
Other	16 (3.7%)
Covid-19 related symptoms (assessed at Wave 2)	13 (3.0%)
Tested for Covid-19 (assessed at Wave 2)	14 (3.2%)

Data are presented as means ± standard deviation or numbers (%) if they are at the category level. Body mass index (BMI) was classified according to the U.S. Centers for Disease Control and Prevention's BMI weight status categories: underweight (below 18.5 kg/m^2); normal or healthy weight (18.5–24.9 kg/m^2); overweight (25.0–29.9 kg/m^2); and obese (30.0 kg/m^2 and more).

Table 2 | Changes in physical activity and sedentariness between Waves 1 and 2

	Wave 1		Wave 2			
Variables	Mean	*SD*	Mean	*SD*	*t* (430)	*p*-value
PA MET (MET min/week)	3,323	2,451	2,718	2,205	5.12	<.001
Moderate PA (min/day)	57.15	42.67	46.77	41.37	2.15	<.01
Vigorous PA (min/day)	47.94	41.91	39.47	40.00	3.82	<.001
Active PA (min/day)	157.80	92.73	134.45	90.89	2.97	.003
Walking (min/day)	52.71	47.70	48.21	44.41	1.83	.067
SED (min/day)	367.99	167.01	369.55	152.85	−0.19	.85

p-value refers to *t*-tests between Waves 1 and 2.
Active PA sum of walking, moderate PA, and vigorous PA; *PA* physical activity; *PA MET* PA calculated as metabolic equivalent of task minutes per week; *SD* standard deviation; *SED* sedentary time.

and PA intention was positively related with the change in PA MET.

Model 2 was run to answer Research Question 3. The predictors explain 38% of the variance in the change in PA MET. The relationships between the Model 1 variables and change in PA MET remained significant, while gamification-related features (β = 235.40, *SE* = 90.75, p = .01) were positively associated with the change in PA MET. With increasing perceived importance of gamification-related features of apps, there was a more positive change (i.e., people's activity rather increased). Both motivational and educational features did not predict the change in PA MET (β = −183.00, *SE* = 105.20, p = .083 and β = 81.34, *SE* = 87.84, p = .36, respectively).

To test the robustness of the results, Model 3 further included participants' age, gender, BMI, education, income, marital status, employment, and ethnicity. The model explains 38% of the variance in the change in PA MET. None of the variables that were added to the model had an influence on the change in PA MET, while the same predictors as in Model 2 remained significant.

DISCUSSION

The purpose of the study was to investigate changes in PA during (vs. before) Covid-19-caused lockdown and to assess the relevance of predictors of change, with a focus on PA smartphone apps and their features. The results showed a decrease in PA MET by 18.2%. While PA MET levels were still high during lockdown in our U.S. resident sample against the background of health-enhancing PA recommendations [3], the assessment might have been biased due to overreporting tendencies [35]. The results of the present study also revealed that the use of PA apps may help buffer the decline in PA MET and that gamification-related app features may be particularly helpful.

Theoretical contribution

Given that physical inactivity has been considered as a pandemic itself, one could argue that the world is currently facing two pandemics at the same time [5]. Mobile health technology, such as smartphone PA apps, might help tackle the inactivity pandemic [9, 36], particularly in the light of restrictions in people's access to PA-enhancing sites (e.g., fitness clubs, parks) during Covid-19-caused lockdown. The study provides evidence on whether PA levels have changed during Covid-19-caused lockdown, whether PA app use helps prevent declines in PA, and which app features are particularly helpful in this context.

First, to fill the void of research into how PA is affected by Covid-19-related restrictions [37], we designed a longitudinal study that was timed so that each individual had experienced the lockdown for at least 28 days before they participated in the second-wave survey. The first-wave survey took place before the lockdown. The results of the study showed that moderate PA and vigorous PA decreased (but sedentary times did not increase) during lockdown—despite the fact that several recommendations were issued that aim to encourage people to stay physically active during Covid-19 [7, 29, 38]. While previous studies have reported similar decreases in PA during Covid-19 [15–18], these studies were largely cross-sectional in nature. The studies cannot rule out that within-participant differences drive the change over time. Thus, it remains unclear what contribution the Covid-19 lockdown made to the change in PA. Our study addresses these limitations, using a longitudinal design, and it revealed a decrease of 18.2% when PA is measured in MET. In the present study, there was no increase in sedentariness, despite the fact that home environments may have made it more convenient for people to be sedentary during Covid-19-caused lockdown [5]. The results could be explained by a potential increase in tasks that require nonsedentary behaviors at home.

Second, while the determinants for PA maintenance have been extensively explored [39, 40], studies have rarely considered the role of PA app use, controlling for intentions to be physically active and baseline PA. Controlling for these variables is important because a lack of intent to be active might explain low PA levels (in particular, when there

Table 3 | Predictors of Change in Physical Activity Between Waves 1 and 2: Results of Regression Analyses

	Model 1 (adjusted R^2 = .37)				Model 2 (adjusted R^2 = .38)				Model 3 (adjusted R^2 = .38)			
	β	*SE*	*t*	*p*-value	β	*SE*	*t*	*p*-value	β	*SE*	*t*	*p*-value
PA (T0)	−0.71	0.06	−12.87	<.001	−0.72	0.05	−13.08	< .001	−0.72	0.06	−12.95	<.001
PA intention (T0)	0.13	0.05	2.66	.008	0.13	0.05	2.51	.012	0.12	0.05	2.44	.015
PA app use	15.68	7.84	2.00	.046	16.82	8.25	2.04	.042	16.60	8.43	1.97	.049
PA app features												
Motivational					−183.00	105.2	−1.74	.083	−178.7	108.5	−1.65	.99
Educational					81.34	87.84	0.93	.355	86.3	89.80	0.96	.34
Gamification related					235.40	90.75	2.59	.010	214.9	95.57	2.25	.025
Age									13.36	10.19	1.31	.19
Gender									−118.3	195.8	−0.96	.34
BMI									−18.98	17.45	−1.09	.28
Education												
Dummy 1									−63.90	364.0	−0.18	.86
Dummy 2									−57.52	322.1	−0.18	.86
Dummy 3									−123.9	376.1	−0.33	.74
Dummy 4									−493.7	705.9	−0.70	.49
Marital status												
Dummy 1									−65.62	228.0	−0.29	.77
Dummy 2									403.5	424.8	0.95	.34
Dummy 3									−399.7	1,017.6	−0.39	.70
Income												
Dummy 1									363.1	443.9	−1.16	.25
Dummy 2									40.82	410.8	0.10	.92
Dummy 3									206.3	434.5	0.47	.64
Dummy 4									591.3	459.4	1.29	.20
Dummy 5									589.9	437.2	1.35	.18
Employment												
Dummy 1									346.6	361.1	0.96	.34
Dummy 2									−215.1	399.8	−0.54	.59
Ethnicity												
Dummy 1									−179.9	366.3	−0.49	.62
Dummy 2									−389.2	393.3	−0.99	.32
Dummy 3									−380.6	514.0	−0.74	.46

Dummy variables were created for categorical and ordinal variables (education: Dummy 1 was coded 1 for Associate's degree, Dummy 2 for College Bachelor's degree, Dummy 3 for Master's degree, and Dummy 4 for PhD; marital status: Dummy 1 was coded 1 for married, Dummy 2 for divorced, and Dummy 3 for widowed; income: Dummy 1 was coded 1 for $25,000–34,999, Dummy 2 for $35,000–49,999, Dummy 3 for $50,000–64,999, Dummy 4 for $65,000–79,999, and Dummy 5 for $80,000 and above; employment: Dummy 1 was coded 1 for self-employment and Dummy 2 for unemployment; ethnicity: Dummy 1 was coded 1 for Black/African American, Dummy 2 for Asian, and Dummy 3 for others).

β regression coefficient; *BMI* body mass index; *PA* physical activity; *SE* standard error; *T0* Wave 1.

are few opportunities to be active, such as during lockdown [5]) and because the baseline level of PA might influence how individuals respond to changes in the environment [41]. Our study revealed a positive effect of the usage of PA apps. Although previous meta-analyses indicated poor adherence and modest effects by using PA apps to increase PA in the long run [9, 42], any increase of PA, regardless of the intensity, was shown to be associated with reduced health risks [43].

Lastly, while there is research on the general effectiveness of PA apps [9, 42, 44] there are few answers to the question regarding which app features are effective to maintain PA. The present study revealed that gamification-related app features particularly helped individuals remain active during Covid-19-caused lockdown. The findings thus help deepen our understanding of the role of app features for helping people maintain their PA during pandemics.

Practical contribution

The study provides implications for individuals and health professionals, as well as policymakers. With regard to individuals, they can be recommended to use PA apps, and particularly those with gamification features, to maintain their PA levels during a pandemic; this reduces health risks and increases well-being [45]. With regard to health professionals, they can be recommended to use apps to engage with their customers. Gamification-related features might need constant updates to arouse individuals, so health professionals might look for gamification elements that help people to both use the app and remain active. Lastly, regarding policymakers in public health, they can be recommended to fight decreases in PA during lockdown to establish a healthy environment during Covid-19 [7] by collaborating with stakeholders from the digital world, such as smartphone and PA app providers. These collaborations might be directed at increasing the pleasure of using technology and being physically active when access to PA-enhancing external resources is limited.

Limitations and future research

This study has some limitations. First, we relied on self-reports to assess PA. Studies have reported substantial differences between self-reports and objective measures for several reasons (e.g., biases and lack of memory) [46]. In a systematic review, it was shown that the IPAQ-SF overestimated actual PA levels by around 84% [35]. Similar arguments can be made for the assessment of app usage. Second, we used a nonrepresentative sample (surveyed online) and only about half of the participants could be recruited in the second wave. While online surveying is an eligible tool during times of social distancing, the generalizability of the results is limited. Also, the results might be biased, because individuals who could not be recruited again may have displayed different behaviors than individuals who participated in both waves. Lastly, the study did not consider the long-term effects of Covid-19 on PA and focused on the time period of lockdown. Previous studies have considered longer time frames. For example, the lasting impact of the 2011 earthquake in East Japan on PA was assessed in a longitudinal study over a time period of 3 years [47]. Future research may look at how PA opportunities have changed in response to the Covid-19 pandemic and how PA levels are affected in the long run.

CONCLUSION

The Covid-19 lockdown decreased U.S. residents' PA MET levels by 18.2%. Using PA apps (and particularly those rated highly on gamification-related features) may help buffer the decline over a time period of several weeks. The robustness of these findings should be tested using objective PA assessments, as well as actual usage behavior of apps and their features.

SUPPLEMENTARY MATERIAL

Supplementary material is available at *Translational Behavioral Medicine* online.

Supplementary Table 1. Start and end dates of the two-wave data collection, based on the U.S. state-level lockdown orders.

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Compliance with Ethical Standards

Conflicts of Interest: The authors declare that they have no conflict of interest.

Authors' Contributions: Y.Y. contributed to the study design, data collection, processing, and analysis and wrote the first draft. J.K. contributed to the study design, data analysis, and edited drafts and served as the principal investigator of this study.

Ethical Approval: All procedures performed in studies involving human participants were in accordance with the ethical standards of the Faculty Board of the TUM Germany, which acts as the local ethics committee for studies outside the TUM Faculty of Medicine, and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This article does not contain any studies with animals performed by any of the authors.

Informed Consent: Informed consent was obtained from all individual participants included in the study.

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Essay 2: Electronic Appendix

Manuscript title: Determinants of physical activity maintenance during the Covid-19 pandemic: a focus on fitness apps

Authors: Yanxiang Yang, Joerg Koenigstorfer

Journal title: Translational Behavioral Medicine

Supplementary Table 1. Start and end dates of the two-wave data collection, based on the U.S. state-level lockdown orders.

U.S. state	Wave 1, T0 (MM.DD.YY)	Begin of lockdown (MM.DD.YY)	Wave 2, T1 (MM.DD.YY)	Duration between waves (days)
Alabama	03.12.20	04.04.20	05.02.20	51
Alaska	03.12.20	03.28.20	04.25.20	44
Arizona	03.12.20	03.31.20	04.28.20	47
California	03.12.20	03.19.20	04.16.20	35
Colorado	03.12.20	03.26.20	04.23.20	42
Columbia	03.12.20	03.30.20	04.27.20	46
Connecticut	03.12.20	03.23.20	04.20.20	39
Delaware	03.12.20	03.24.20	04.21.20	40
Florida	03.12.20	04.03.20	05.01.20	50
Georgia	03.12.20	04.03.20	05.01.20	50
Hawaii	03.12.20	03.25.20	04.22.20	41
Idaho	03.12.20	03.25.20	04.22.20	41
Illinois	03.12.20	03.21.20	04.18.20	37
Indiana	03.12.20	03.25.20	04.22.20	41
Kansas	03.12.20	03.30.20	04.27.20	46
Kentucky	03.12.20	03.26.20	04.23.20	42
Louisiana	03.12.20	03.23.20	04.20.20	39
Maine	03.12.20	04.03.20	04.30.20	49
Maryland	03.12.20	03.30.20	04.27.20	46
Massachusetts	03.12.20	03.24.20	04.21.20	40
Michigan	03.12.20	03.24.20	04.21.20	40
Minnesota	03.12.20	03.27.20	04.24.20	43
Mississippi	03.12.20	04.03.20	05.01.20	50
Missouri	03.12.20	04.06.20	05.04.20	53
Montana	03.12.20	03.28.20	04.24.20	44
Nevada	03.12.20	04.01.20	04.29.20	48
New Hampshire	03.12.20	03.27.20	04.24.20	43
New Jersey	03.12.20	03.21.20	04.18.20	37
New Mexico	03.12.20	03.24.20	04.21.20	40

New York	03.12.20	03.22.20	04.19.20	38
North Carolina	03.12.20	03.30.20	04.27.20	46
Ohio	03.12.20	03.23.20	04.20.20	39
Oklahoma	03.12.20	04.02.20	04.30.20	49
Oregon	03.12.20	03.23.20	04.20.20	39
Pennsylvania	03.12.20	04.01.20	04.29.20	48
Rhode Island	03.12.20	03.28.20	04.25.20	44
South Carolina	03.12.20	04.07.20	05.05.20	54
Tennessee	03.12.20	04.02.20	04.30.20	49
Texas	03.12.20	04.02.20	04.30.20	49
Vermont	03.12.20	03.25.20	04.22.20	41
Virgin Islands	03.12.20	03.25.20	04.22.20	41
Virginia	03.12.20	03.30.20	04.27.20	46
Washington	03.12.20	03.23.20	04.20.20	39
West Virginia	03.12.20	03.23.20	04.20.20	39
Wisconsin	03.12.20	03.25.20	04.22.20	41

Note. T0: Start date of the first wave of survey; T1: Start date of the second wave of survey (equivalent to 28 days after the lockdown had begun; in all states, the lockdown was ongoing at T1); time duration: T1 – T0.

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Essay 3

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REVIEW ARTICLE

Effects of Gamified Smartphone Applications on Physical Activity: A Systematic Review and Meta-Analysis

Yanxiang Yang, MSc, Huijun Hu, BA, Joerg Koenigstorfer, PhD

Introduction: This systematic review and meta-analysis aims to examine the impacts of standalone gamified smartphone application-delivered interventions on physical activity.

Methods: Web of Science, Scopus, PubMed, PsycINFO, and ACM Digital Library were searched for publications that were published between January 1, 2008 and August 31, 2021. Eligibility criteria were RCTs or single-arm pre-to-post interventions delivered by standalone gamified applications and targeting physical activity. Study-specific results were analyzed using random-effects meta-analysis, with a standardized mean difference. Meta-regressions, subgroup analyses, and sensitivity analyses were performed. PRISMA guidelines were followed, and the Grading of Recommendations Assessment, Development and Evaluation system was used to determine the strength of the evidence.

Results: A total of 19 studies with 24 gamified applications were eligible, and 16 studies were included in the meta-analysis. Standalone gamified applications had a small-to-moderate effect on physical activity in both the between-group RCTs (n=12 applications, standardized mean difference=0.34, 95% CI=0.06, 0.62, I^2=72%, p<0.01; Grading of Recommendations Assessment, Development and Evaluation: moderate) and the within-group pre-to-post interventions (n=18 applications, standardized mean difference=0.38, 95% CI=0.17, 0.59, I^2=74%, p<0.01; Grading of Recommendations Assessment, Development and Evaluation: very low). Leave-one-out sensitivity analyses sustained the main effects with lower heterogeneity (I^2 of 31.0% and 47.8%, respectively).

Discussion: Using gamified smartphone applications as standalone interventions may increase physical activity. Future research could investigate the impacts of gamified applications on physical activity by isolating the role of specific single or clustered groups of application features.
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INTRODUCTION

Physical activity of any intensity has been proven to help prevent and manage several chronic diseases and improve health.[1,2] Despite this, many adults and adolescents fail to achieve the recommended levels of physical activity.[3] Technology-based tools have been developed to help individuals initiate and maintain physical activity. Smartphone applications (apps) are regarded as particularly promising,[4] although their effectiveness might be modest and impaired by poor user adherence.[5,6] Therefore, strategies are needed to increase the effectiveness of physical activity interventions delivered by smartphone apps.[7]

Gamification is a prominently used design strategy in promoting physical activity.[8] *Gamification* is defined as the use of game design elements in non-game contexts.[9] Gamification commonly incorporates features,[10] also referred to as affordances,[11] such as storytelling, the

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implementation of challenges that need to be mastered, and points to be collected.[9,12] In the context of fitness, gamified apps include features to increase user motivation, particularly intrinsic motivation (i.e., the joy of performing the activity per se), and sustain physical activity habits over time.[13] Although gamification features have been widely implemented in health and fitness apps,[14−16] they often insufficiently rely on behavioral theories,[14] behavior change techniques (BCTs),[15] or behavioral economic principles.[16]

The literature on gamification and physical activity lacks systematic reviews and meta-analyses of studies that assess the impacts of standalone gamified apps on physical activity. One previous systematic review presented an overview of the appropriateness of gamified apps for physical activity.[7] The authors emphasized the importance of gamified app usage in physical activity as a new research field, where the effectiveness could neither be determined nor subjected to meta-analysis. Another systematic review assessed whether previous studies revealed positive, null, or negative effects but did not provide any further quantification.[8] Although the inclusion of multiple intervention factors besides gamification (e.g., studies that added in-person counseling to gamified app interventions) benefited the pooled effect size, it also increased the between-study heterogeneity. Importantly, none of the previous reviews[7,8,17,18] focused on standalone gamified apps (i.e., without additional supervision or support) or exclusive app use (i.e., without additional intervention types). Assessing the impacts of standalone gamified apps on physical activity is important to study cause-effect relationships without influence from confounds. Indeed, most individuals use their apps without any additional support. Furthermore, it has been claimed that entirely app-based interventions are cost effective to be generalized in free-living conditions.[19]

This systematic review and meta-analysis aims to synthesize the effects of standalone gamified smartphone app-delivered interventions on physical activity in both RCTs and single-arm pre-to-post interventions. Given the need to promote physical activity in all age groups, this study does not limit its analysis to 1 particular age group.

METHODS

This study follows the PRISMA guidelines[20] and the Cochrane Collaboration handbook.[21] The review protocol was registered with the International Prospective Register of Systematic Reviews (CRD42020209502).

Search Strategy

A systematic search was performed in 5 databases (Web of Science, Scopus, PubMed, PsycINFO, and ACM Digital Library) through August 31, 2021. The publication year was restricted to the period beginning in 2008 when the term *gamification* originated in the literature.[9] The search was restricted to peer-reviewed journal or conference articles with English full texts. The search string combined 3 groups of keywords: *gamification, smartphone app*, and *physical activity* (details are in Appendix Table 1, available online). Serious games, video games, or exergames were excluded from the review. Forward and backward tracking was performed by examining the reference list of relevant articles.

Eligibility Criteria

This review included studies based on the predetermined Population, Intervention, Comparison, Outcomes, and Study design criteria.[21] Specifically, studies were eligible if they meet the following conditions: (1) population of any health status and age (adults, children, or adolescents were considered, given the need to promote physical activity in all age groups[2]); (2) interventions are standalone (with no additional supervision or support) gamified smartphone apps targeting physical activity; (3) comparisons are either control groups in RCTs or pre-to-post measures of single-arm intervention groups; and (4) outcomes are indicators of physical activity.

Study Collection and Data Extraction

Duplicates of the records were excluded. Titles, abstracts, and full texts were screened independently by the first (YY) and second (HH) authors. Any disagreements were discussed with the last author (JK) until a consensus was reached. The information on the included studies was then extracted into a Microsoft Excel, version 16.44, spreadsheet.

For qualitative synthesis, the following information was extracted: author name and publication year, study region, study design, participants' demographics, information concerning the gamified app, design and duration of intervention, and physical activity outcome. The gamification features used in the smartphone apps were extracted according to an established framework of features[11] adapted to the context of this research. In particular, this study considered core gamification features from the following domains: achievement (e.g., leaderboards and rankings, points, and scores—features whose main purpose is to increase users' competency, mastery, and growth) and immersion (e.g., storytelling and use of avatars—features whose main purpose is to immerse the user in a self-directed inquisitive activity). Additionally this paper refers to leveraging gamification features; they have the potential to enhance the gamification experience. Examples of leveraging features are social networking, real-world interactions, as well as reminders and notifications. The associated BCTs[22] were identified on the basis of authors' arguments as well as the conceptual origin of the respective feature and their linkage with specific BCTs.[15,23]

For the pooled meta-analysis, the means and SDs of the pre-to-post interventions were extracted. For studies that only provided either SEs and 95% CIs or medians and IQRs, the means and SDs were calculated using equations suggested by the Cochrane Collaboration handbook.[21] The mean values of sedentary time were multiplied by −1 to ensure that their effects had the same direction as those of other physical activity outcomes.[21] When studies involved multiple outcomes, only 1 main outcome (determined by the study's main purpose) was used for the main meta-analysis.

When studies considered ≥2 intervention groups, only the one using a gamified app was included. Data from 4 studies[24−27] were extracted at the authors' request. The data extraction was performed by the first 2 authors (YY and HH) and cross-checked by the last author (JK).

Risk of Bias Assessment

Two reviewers (YY and HH) independently assessed the risk of bias and resolved any disagreements by consensus with another reviewer (JK). The Risk of Bias 2[28] was used for the RCTs (n=17), and the Risk of Bias in Non-randomized Studies of Interventions[29] was used for the single-arm pre-to-post interventions (n=2).

Meta-Analysis

First, between-group analyses examined the differences between intervention and control groups for the RCTs. Second, within-group analyses assessed the changes from pre-to-post interventions among all the intervention groups in the included studies. Standardized mean differences (SMDs) were calculated on the basis of the different physical activity outcomes and units. Hedge's g values of 0.2, 0.5, and 0.8 represent small, moderate, and large effect sizes, respectively.[21] A random-effects model was used on the basis of the assumption of different true effect sizes.[21] SMDs were back transformed to original units of measures for step counts (steps/day) and moderate-to-vigorous physical activity (minutes/day) to extrapolate the estimated effect size.[30] Statistical heterogeneity was tested with I^2 and p-value for the Q statistic. I^2 values of 25%, 50%, and 75% indicate small, medium, and large degrees of heterogeneity, respectively.[21] Publication bias was assessed by Egger's test[31] and was visually presented with contour-enhanced funnel plots to differentiate any sources of asymmetry (e.g., due to publication bias), where necessary.[32] The levels of evidence for the primary outcomes were assessed using the Grading of Recommendations Assessment, Development and Evaluation (GRADE) guidelines[33] (the detailed methodology is presented in Appendix Table 6, available online). All statistical analyses were performed with R studio software, version 1.4.1103, and the meta-analysis was conducted with the meta package.[34]

Meta-Regression, Subgroup, and Sensitivity Analyses

Two meta-regressions were performed: one for intervention durations and another for sex (% female). A total of 6 subgroup analyses were conducted for the different study populations (healthy, patients), age groups (children and adolescents, adults, older adults), study designs (RCT, single arm; within group only), physical activity measurements (rather subjective, rather objective), physical activity outcomes (moderate-to-vigorous physical activity, step counts), and type of control group (waitlisted, active control; between-group only). The selection of the moderators was inspired by previous publications.[23] Significance levels were set at 0.1 for subgroup analyses[35] and 0.05 for meta-analyses and meta-regressions.[21] A total of 3 sensitivity analyses were performed: (1) the leave-one-out analysis for 1 study[36] with potential heterogeneity, (2) an analysis after removal of 2 studies[24,37] with a high overall risk of bias, and (3) an analysis that only included studies with ≥4 low risk of bias categories.[38]

RESULTS

The initial database search yielded 1,268 records after removal of duplicates (Figure 1). After further title and abstract screening, 101 records were retrieved for full-text assessment. On the basis of the Population, Intervention, Comparison, Outcomes, and Study criteria, 82 articles were excluded (Appendix 1, available online, includes the full list of excluded studies with reasons). Inter-rater reliability was good (κ statistic of 0.68) for the full-text assessment before reaching consensus among reviewers (Appendix 2, available online). A total of 19 studies[24−27,36,37,39−51] were finally included in the systematic review, and 16 studies[24−27,36,39−45,47,48,50,51] provided sufficient data for the meta-analysis.

Study Characteristics

The 19 studies included in this systematic review were published between 2014 and 2021 (Appendix Table 2, available online). A total of 17 studies were RCTs, and 2 were single-arm pre-to-post interventions.[40,41] Participants were children and adolescents (2 studies), adults (15 studies), and elderly (2 studies). Two studies were conducted with patients,[36,47] and the remainder were with healthy people. The overall sample size was 1,908 (median=67 per study, range=18−354). All interventions were delivered by standalone gamified apps. For the RCTs, 6 were waitlisted control studies, and 11 were active control studies. The gamified apps were either self-designed (13 studies) or commercially available (6 studies). The duration of the intervention ranged between 1 and 24 weeks (median=7 weeks). Physical activity was measured either rather objectively (e.g., accelerometers, activity trackers, smartphone built-ins; 13 studies), rather subjectively (e.g., questionnaires; 2 studies), or with both types of assessments (4 studies). The main outcomes were moderate-to-vigorous physical activity and step counts. The quality assessment revealed some concerns (15 studies), whereas 2 studies were of high quality,[44,50] and 2 were of low quality.[24,37] Most of the studies were RCTs (17 of 19), in which 12 studies had ≥4 low categories of risk of bias. The full results of the quality assessment are provided in Appendix Table 4 (available online).

Gamification Features

A total of 24 gamified apps were used in the 19 studies (Appendix Table 3, available online). In most of the apps, multiple features were input (from 1 to 9, a median of 4 per app). Figure 2 illustrates the frequency of 12 core gamification features that were identified (besides 7 leveraging features). In-game rewards, leaderboards and rankings, virtual teams and cooperation, and points and scores were the most frequently used core features for

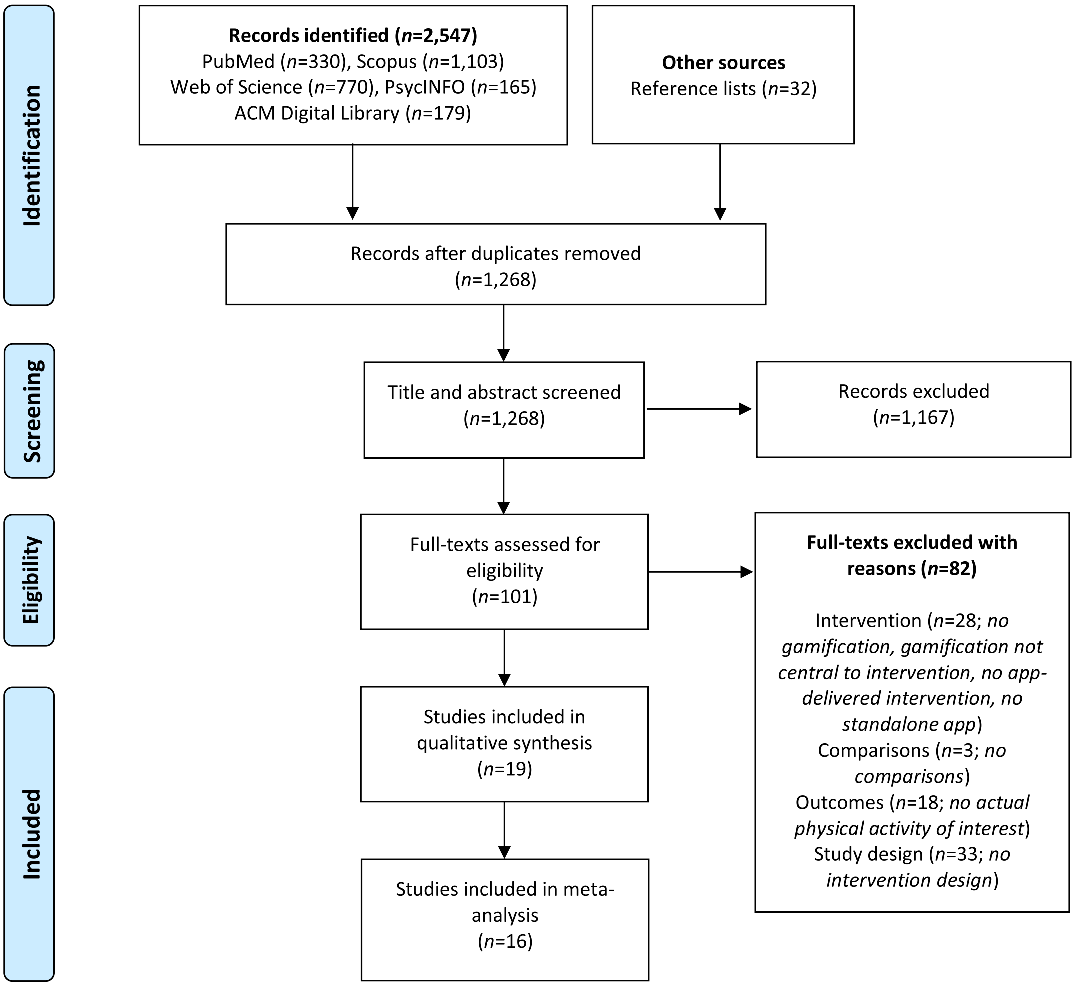


Figure 1. Flowchart of the included studies.

gamification (with an overall frequency of 4–14 and a median of 6.5). The most frequently implemented BCTs in the 19 studies were imaginary reward, comparison of behavior, and social support (Appendix Table 3, available online).

Primary Meta-Analyses

In the between-group RCTs, the gamified smartphone apps had a small-to-moderate effect on physical activity (n=12 apps, SMD=0.34, 95% CI=0.06, 0.62, p<0.01; GRADE: moderate) (Figure 3). In the within-group pre-to-post interventions, the gamified smartphone apps had a small-to-moderate effect on physical activity (n=18 apps, SMD=0.38, 95% CI=0.17, 0.59, p<0.01; GRADE: very low). The high heterogeneity identified in both groups (I^2 of 72% and 74%, respectively) implies the importance of considering further moderators and sensitivity analyses. The results of the GRADE evidence are provided in Appendix Table 6 (available online).

Meta-Regression, Subgroup, and Sensitivity Analyses

Figure 4 summarizes the results of the meta-regressions and subgroup analyses for the between-group RCTs and within-group pre-to-post interventions. In the meta-regressions, the effects of gamified apps on physical activity were significantly modified by the duration of the intervention (n=12 apps, SMD=0.05, p=0.006; positive effects with increasing duration) as well as sex (n=12 apps, SMD= −0.01, p=0.036; positive effects for male [versus female] participants) in the between-group RCTs. No significant effects were identified in the within-group meta-regressions (p>0.05).

In the between-group RCTs subgroup analyses, the effects were significantly modified by the study populations (with smaller, yet positive effects for healthy people [versus for patients], p=0.09). In the within-group pre-to-post interventions subgroup analyses, larger effects were identified for step counts (n=8 apps, SMD=0.69)

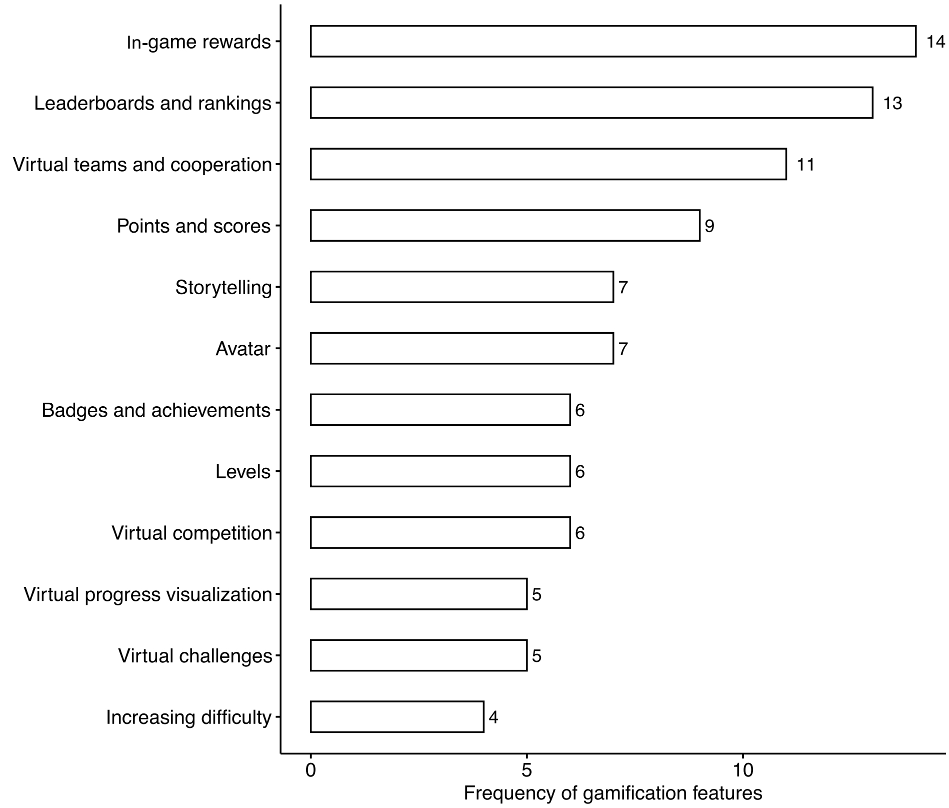


Figure 2. Prevalence of gamification features.
Note: The following leveraging features were identified: social networking (10), performance stats and feedback (9), goal setting (7), reminders and notifications (6), real-world interaction (5), peer rating (3), and personalization (1).

than for moderate-to-vigorous physical activity (n=10 apps, SMD=0.18, p=0.03).

A total of 3 sensitivity analyses (Appendix Table 5, available online) were conducted. The results were conducted. The results showed that the positive effects in the main analyses remained, supporting the overall results with a higher degree of certainty, with 1 exception: for studies with <4 low categories of risk of bias in the between-group studies, the effect was not significant using the conventional 0.05 cut off values for significance (p=0.095).

Publication Bias

Contour-enhanced funnel plots and Egger's tests are presented in Appendix Figure 2 (available online). Egger's tests were nonsignificant for the between-group (t[df]=1.62 [10], p=0.14) and within-group (t[df]=1.61 [16], p=0.13) studies. They remained nonsignificant after the leave-one-out sensitivity analyses (between-group studies: t[df]=0.87 [9], p=0.41; within-group studies: t[df]=0.45 [15], p=0.66). The results indicated no publication bias.[31]

Secondary Meta-Analysis

Further secondary meta-analyses were performed separately for each physical activity outcome in the within-group and between-group studies (Appendix Figure 1, available online). In the between-group studies, the effects of the gamified apps were significant for walking (n=3 apps, SMD=0.64, 95% CI=0.31, 0.96), with moderate-quality evidence. In within-group studies, the effects of gamified apps were significant for moderate-to-vigorous physical activity (n=10 apps, SMD=0.13, 95% CI=0.00, 0.25; GRADE: very low), step counts (n=10 apps, SMD=0.61, 95% CI=0.23, 0.98; GRADE: very low), total physical activity (n=2 apps, SMD=0.45, 95% CI=0.02, 0.88; GRADE: very low), and walking time (n=2 apps, SMD=0.77, 95% CI=0.39, 1.14; GRADE: very low). The analyses, in which SMDs were converted to original units, revealed an increase of 2,393 steps/day (95% CI=422, 4,361) in the between-group studies and of 2,839 steps/day (95% CI=1,270, 4,408) in the within-group studies and an increase in moderate-to-vigorous physical activity of 23.3 minutes/day (95% CI=4.1, 42.5) and 40.6 minutes/day (95% CI=18.2, 63.1) (Appendix 3, available online).

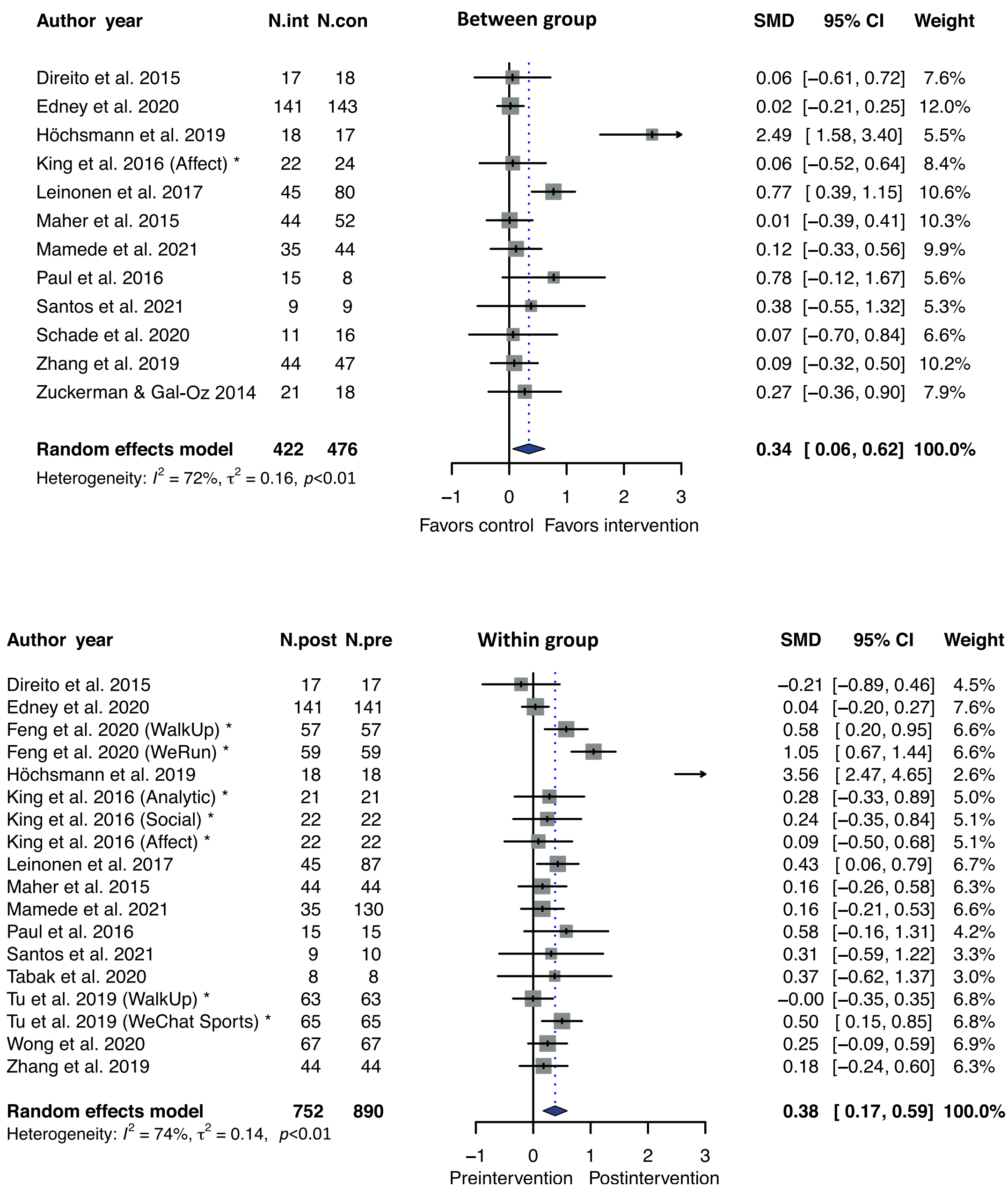
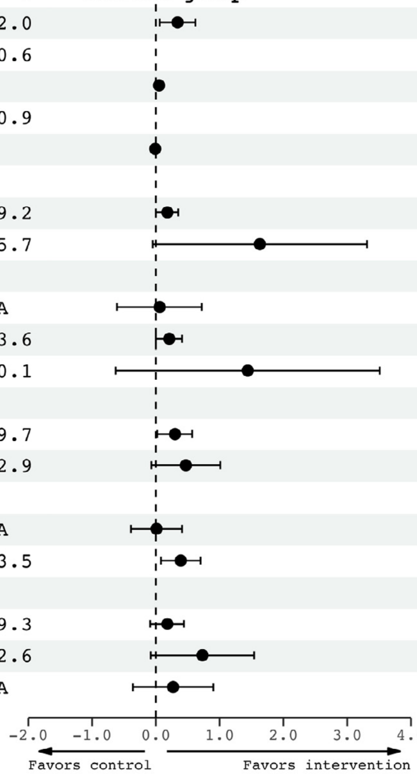


Figure 3. Overall effect size (SMD) and 95% CIs for the effects of standalone gamified smartphone apps on physical activity.
Note: *Multiple apps were used within one study. For studies with multiple physical activity outcomes, only one main outcome (e.g., MVPA, step counts) was extracted for the main analyses as defined in the methods.
Abbreviations: app, application; SMD, standardized mean difference; N.int, sample size in the intervention group; N.con, sample size in the control group; MVPA, moderate-to-vigorous physical activity.

DISCUSSION

This is the first systematic review and meta-analysis to examine the impacts of standalone gamified smartphone apps on physical activity. Although other authors have conducted meta-analyses on the influence of app usage on physical activity, they did not specifically look at gamification and included not only apps but also mobile health and fitness devices, such as trackers, as well as studies in which supervision and counseling were provided, beside app-based interventions.[23,52] Therefore, the effects of standalone gamified apps have remained unknown until now. A total of 12 gamification features from 24 gamified apps were identified in RCTs and

Moderator	p	Studies	I^2 %	Between group	Estimate
All	<0.01	12	72.0		0.34 (0.06 to 0.62)
Duration (weeks)	0.006		60.6		
3 to 24		12			0.05 (0.01 to 0.08)
Gender (F%)	0.036		60.9		
0 to 100%		12			-0.01 (-0.02 to -0.00)
Population	0.09				
Healthy		10	29.2		0.18 (0.00 to 0.35)
Patients		2	85.7		1.63 (-0.05 to 3.31)
Age	0.46				
Children		1	NA		0.06 (-0.61 to 0.72)
Adults		9	43.6		0.21 (0.00 to 0.41)
Elderly		2	90.1		1.44 (-0.63 to 3.51)
Different control	0.57				
Active control groups		6	39.7		0.30 (0.02 to 0.57)
Waitlist group		6	82.9		0.47 (-0.07 to 1.01)
PA measurement	0.14				
Rather subjective		1	NA		0.01 (-0.39 to 0.41)
Rather objective		11	73.5		0.39 (0.08 to 0.70)
PA outcome	0.44				
MVPA		6	59.3		0.18 (-0.09 to 0.44)
Step counts		5	82.6		0.73 (-0.08 to 1.54)
Walking		1	NA		0.27 (-0.36 to 0.90)



Moderator	p	Studies	I^2 %	Within group	Estimate
All	<0.01	18	74.0		0.38 (0.17 to 0.59)
Duration (weeks)	0.054		75.3		
3 to 24		18			0.04 (-0.00 to 0.08)
Gender (F%)	0.17		72.9		
0 to 100%		18			-0.01 (-0.02 to 0.00)
Population	0.24				
Healthy		16	50.0		0.29 (0.13 to 0.44)
Patients		2	95.0		2.04 (-0.89 to 4.97)
Age	0.37				
Children		2	30.5		0.11 (-0.30 to 0.53)
Adults		13	57.9		0.32 (0.15 to 0.50)
Elderly		3	91.8		1.40 (-0.60 to 3.40)
Study design	0.98				
RCT		17	75.5		0.38 (0.17 to 0.60)
Single-armed		1	NA		0.37 (-0.62 to 1.37)
PA measurement	0.27				
Rather subjective		2	0.00		0.22 (-0.05 to 0.48)
Rather objective		16	78.0		0.42 (0.17 to 0.66)
PA outcome	0.03				
MVPA		10	0.00		0.18 (0.05 to 0.31)
Step counts		8	85.9		0.69 (0.24 to 1.15)

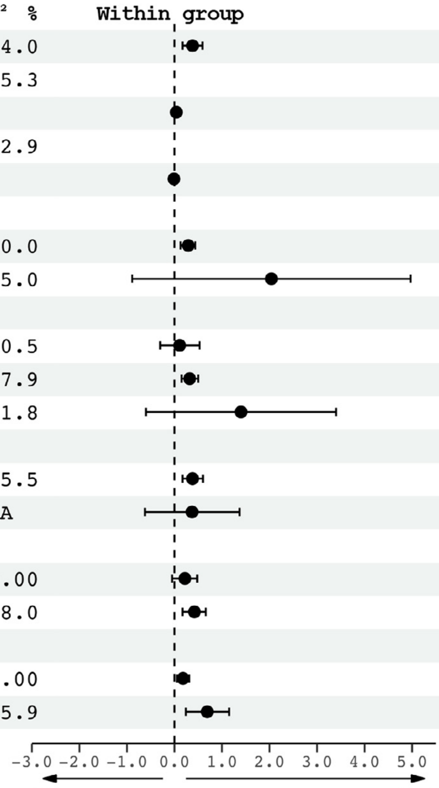


Figure 4. Meta-regressions and subgroup analyses for between- and within-group studies.

single-arm interventions. The use of gamified smartphone apps resulted in a significant increase in physical activity, with a moderate level of evidence for RCTs and a very low level of evidence for pre-to-post interventions. The main effects were significantly modified by intervention duration, sex, population, and physical activity outcomes.

Effects of Standalone Gamified Apps on Physical Activity

The primary meta-analysis found that using gamified smartphone apps as standalone interventions may increase physical activity. The results support findings from previous qualitative systematic reviews of gamification on health and well-being.[8,17,18] Specifically, 2 reviews claimed that gamification has positive effects on health behaviors, including physical activity (59% reported positive effects),[18] reduction in body weight, and maintaining physical activity among children and adolescents.[17] Another systematic review of 16 comparison studies revealed largely positive effects of gamification on physical activity.[8] A methodologic shortcoming of these reviews is that they are all qualitative in nature, with no meta-analyses. This systematic review and meta-analysis partially fills this research gap and presents evidence for the positive impacts of standalone gamified apps on physical activity in free-living conditions. Notably, the very low level of evidence for pre-to-post studies is partly a result of how the classification of observational studies is derived.[33] The GRADE rating does not take into account the fact that 12 of 14 studies in the within-group studies were the intervention arms of RCTs.

Secondary meta-analyses were conducted for different physical activity outcomes. Gamified apps had the largest effects on walking and step counts (SMDs ranging from 0.59 to 0.77) in both between-group and within-group studies. Indeed, most of the gamified apps in the included studies were designed to target step counts (9 studies) and walking.[51] For example, the most popular gamified app for increasing steps and walking—Pokémon Go—had a modest, yet significant effect on daily steps.[53] Steps and walking, in turn, are associated with health benefits.[54,55] However, it should be noted that the secondary meta-analyses considered multiple physical activity outcomes within a single study (e.g., Direito et al.[50] measured 5 outcomes; Appendix Table 2, available online). This leads to duplicated sample size calculations in the meta-analyses.[21] Therefore, the effects of gamified apps on each physical activity outcome were analyzed separately, and no pooled overall effect was calculated.

Gamification Features

A total of 12 gamification features within 24 gamified apps were identified in this systematic review. Previous systematic reviews of studies[7,18,56,57] or app store-based reviews[14,16] have also reported the implementation of gamification features (sometimes referred to as affordances or elements). However, one limitation of these reviews is that they often include leveraging features, so the nature of gamification is diluted.[18,56] Most importantly, 2 systematic reviews of mobile gaming apps on physical activity and mental health found that the game elements most commonly incorporated were, on one hand, virtual rewards, competition, and avatars (range from 2 to 9)[7] and, on other hand, levels or progress feedback, points or scoring, and rewards or prizes.[57] In the app store-based reviews, virtual rewards and challenges, as well as social pressure and goal setting (the latter 2 being leveraging features rather than gamification features, according to the authors' argumentation) were the most used features.[14,16] In these reviews, there were rarely links between gamification features and BCTs. However, as previous app store-based reviews showed, gamification features were (and should be) based on BCTs or other behavioral theories.[15,16] Consequently, this study summarized 12 core gamification features and linked them to BCTs.[11]

Rewards were implemented most frequently in the 19 studies. This finding is consistent with those of previous reviews.[7,18,56] A reward system is regarded as a fundamental component of gamified interventions.[58] Furthermore, most of the gamified apps were designed with leaderboards, which allowed users to see each other's rank and current status. This was often accompanied by a social networking feature (i.e., a leveraging tool). Besides encouraging self-improvement, social features often created a competitive environment in which users could satisfy their motivational needs (e.g., achievement).[59] Indeed, it has been argued that, for long-term motivation, gamification should focus less on rewards (which increase extrinsic motivation) but more on meaningful gamification; that is, increasing intrinsic motivation (in which "users find personal connections that motivate engagement with a specific context for long-term change"[60]).

Note: All: Overall effect size of meta-analysis. Moderator: meta-regression for 2 continuous moderators (duration, sex) and subgroup analyses for 6 categorical moderators. Estimate: regression coefficients (95% CI) for meta-regressions or standardized mean difference (95% CI) for subgroup analyses. *p*-value: Test of moderators (meta-regression) or test of subgroup differences (random-effects model). I^2 %: Indicator of study-specific heterogeneity.
Abbreviations: F, female; MVPA, moderate-to-vigorous physical activity; NA, not applicable; PA, physical activity.

Source of Heterogeneity

The leave-one-out sensitivity analyses resulted in low heterogeneity in both the between-group (31%) and within-group (47.8%) studies, which largely explained the source of the high heterogeneity. In the exploration of moderators, the authors found that a longer intervention duration was positively associated with an increase in physical activity in the between-group RCTs but that the effect was of very small magnitude and driven by a 24-week study[36] that had the largest effect of all included studies. Against the background of previous findings that apps were most effective in increasing physical activity at early stages (i.e., <3 months),[6,23] future research is needed to investigate the impacts of gamified physical activity on sustained physical activity for mid- and long-term time periods. Second, the authors found greater effects for male than for female participants, which may be because male individuals might have had higher technology readiness than female individuals,[61,62] and this might have translated into a higher interest in using technology to promote physical activity. Furthermore, male participants might have been more interested in gamified physical activity, particularly against the background of achievement motives[63] and enjoyment of immersive practices.[64] In addition, female participants might have had a higher need for personal, nondigital relations,[63] and this might be associated with a higher preference for nonapp-based physical activity interventions. Thus, gamified apps might need to be designed differently for female and male participants owing to differences in needs and motives. Research on the acceptance of gamified apps is required to study the factors that attract female (versus male) users to initially download and try an app. Thirdly, the effects were modified by the study population in the between-group RCTs and by different physical activity outcomes in the within-group pre-to-post interventions. The moderators of age, study design, and physical activity measurement did not reach significance levels. These null-modifying effects suggest that gamified apps have positive effects on physical activity for all participant ages across all design types and for physical activity measured by devices (rather objectively) or self-reported (rather subjectively).

Implications and Future Research

The main finding of this systematic review and meta-analysis—the positive impacts of standalone gamified smartphone apps on physical activity—supports the potential relevance of the WHO's strategy of promoting the development and implementation of digital technologies to improve physical activity around the world.[65] In addition, the results have important implications for health professionals. They may design effective unsupervised gamified digital interventions in free-living conditions. Furthermore, the findings are important for gamification research on physical activity because standalone apps with gamification features can be used to promote physical activity. However, researchers should be reminded to provide clear definitions and measurements for gamification features. Because it remains largely unclear how long changes in physical activity last or which gamification features sustain behavior change, longitudinal studies using several waves of data collection are needed. Finally, valid and reliable measurement tools for physical activity should be used. For example, the use of the smartphone itself as an objective measure of physical activity has been criticized because of well-documented limitations.[5]

Limitations

This study has several limitations. Firstly, both RCTs and single-arm pre-to-post interventions were included, with the latter partially explaining the very low level of evidence. Secondly, high heterogeneity was observed in the pooled analyses, which may be explained by the differences in intervention designs. The measurement tools for physical activity differed greatly between the studies and introduced biases. When combined with trackers, apps might be more effective, simply because wearing trackers reminds participants of the need to be physically active. Thirdly, most apps mixed several gamification features. The underlying mechanisms of specific features and their interactions should be investigated to identify those features that drive the effectiveness of gamified apps. The same arguments can be made for the effectiveness of different BCTs that were identified in this review. In a fourth limitation, this paper relied on established features of gamification. However, a focus on meaningful gamification has been proposed, where play, exposition, choice, information, engagement, and reflection may be relevant.[60] Unfortunately, the authors of the 19 studies that were reviewed did not build on this framework, and the study descriptions mostly did not allow for this analysis to draw inferences about the implementation of these alternative features. As a fifth limitation, there were slight deviations from the protocol; all of them helped in the achievement of the research goals (Appendix 4, available online). Finally, the authors were unable to perform a meta-analysis for 3 included studies[37,46,49] because the necessary data were not available.

CONCLUSIONS

The use of gamified smartphone apps as standalone interventions may increase physical activity. Future research could investigate the impacts of gamified apps on physical activity by isolating the effects of specific features, thus ruling out the potentially confounding influences of multiple features within a single investigation.

CREDIT AUTHOR STATEMENT

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SUPPLEMENTAL MATERIAL

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Essay 3: Electronic Appendix

Manuscript title:	Effects of Gamified Smartphone Applications on Physical Activity: A Systematic Review and Meta-Analysis
Authors:	Yanxiang Yang, Huijun Hu, Joerg Koenigstorfer
Journal title:	American Journal of Preventive Medicine

APPENDIX 1. LIST OF EXCLUDED PUBLICATIONS AFTER FULL-TEXT REVIEW (PICOS CRITERIA)

PICOS (n=82)

Population (n=0):
NA.

Intervention (n = 28):

- No gamification was considered (e.g., pure games, active video games, exergames) (n=3)
- Gamification was not the main intervention (n=8)
- No app-delivered gamification intervention was considered (n=12)
- No standalone gamified app was considered (n=5)

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Blackman KC, Zoellner J, Kadir A, et al. Examining the feasibility of smartphone game applications for physical activity promotion in middle school students. *Games Health J.* 2015;4(5):409–419. https://doi.org/10.1089/g4h.2014.0120.

Broom DR, Flint SW. Gotta catch ‘em all: Impact of Pokemon Go on physical activity, sitting time, and perceptions of physical activity and health at baseline and three-month follow-up. *Games Health J*. 2018;7(6):401–408. https://doi.org/10.1089/g4h.2018.0002.

Burkow TM, Vognild LK, Johnsen E, Bratvold A, Risberg MJ. Promoting exercise training and physical activity in daily life: A feasibility study of a virtual group intervention for behavior change in COPD. *BMC Med Inform Decis Mak*. 2018;18:136. https://doi.org/10.1186/s12911-018-0721-8.

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Dadaczynski K, Schiemann S, Backhaus O. Promoting physical activity in worksite settings: Results of a German pilot study of the online intervention Healingo fit. *BMC Public Health*. 2017;17:696. https://doi.org/10.1186/s12889-017-4697-6.

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Koskimäki H, Siirtola P, Keskitalo E, et al. Computer game and wearable sensors based approach to promote physical activity for young men. *Proceedings of the ACM International Joint Conference and International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers.* 2017;512–517. https://doi.org/10.1145/3123024.3124433.

Lin PJ, Fanjiang YY, Wang JK, et al. Long-term effectiveness of an mHealth-tailored physical activity intervention in youth with congenital heart disease: A randomized controlled trial. *J Adv Nurs*. 2021. https://doi.org/10.1111/jan.14924.

Marquet O, Alberico C, Hipp AJ. Pokémon Go and physical activity among college students. A study using Ecological Momentary Assessment. *Comput Human Behav*. 2018;81:215–222. https://doi.org/10.1016/j.chb.2017.12.028.

Ni MY, Hui RWH, Li TK, et al. Augmented reality games as a new class of physical activity interventions? The impact of Pokémon Go use and gaming intensity on physical activity. *Games Health J.* 2019;8(1):1–6. https://doi.org/10.1089/g4h.2017.0181.

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Vella K, Peever N, Klarkowski M, Ploderer B, Mitchell J, Johnson D. Using applied games to engage mHealth users: A case study of MinDMax. *Proceedings of the Annual Symposium on Computer-Human Interaction in Play.* 2018;511–522. http://doi.org/10.1145/3242671.3242686.

Walsh G, Golbeck J. StepCity: A preliminary investigation of a personal informatics-based social game on behavior change. *Proceedings of the 32nd Annual ACM Conference on Human Factors in Computing Systems*. 2014;2371–2376. https://doi.org/10.1145/2559206.2581326.

Wu Y, Kankanhalli A, Huang KW. Gamification in fitness apps: How do leaderboards influence exercise? *Proceedings of the 36th International Conference on Information Systems.* 2015;1–12.

Comparisons (n=3):

- No comparisons were made (e.g., observational user data or surveys only) (n=3)

Althoff T, White RW, Horvitz E. Influence of Pokémon Go on physical activity: Study and implications. *J Med Internet Res.* 2016;18(12):e315. https://doi.org/10.2196/jmir.6759.

Liu W, Ligmann-Zielinska A. A pilot study of Pokémon Go and players' physical activity. *Games Health J*. 2017;6(6):343–350. https://doi.org/10.1089/g4h.2017.0036.

Ma BD, Ng SL, Schwanen T, et al. Pokémon Go and physical activity in Asia: Multilevel study. *J Med Internet Res*. 2018;20(6):e217. https://doi.org/10.2196/jmir.9670.

Outcomes (n = 18):

- No actual physical activity was considered (e.g., user engagement, physical activity intention, and movement skills) (n=12)
- Physical activity was not of main interest (e.g., main interest was on app development or app feasibility testing) (n=6)

Bovonsunthonchai S, Ariyaudomkit R, Susilo TE, et al. The impact of different mobile phone tasks on gait behavior in healthy young adults. *J Transp Health*. 2020;19:100920. https://doi.org/10.1016/j.jth.2020.100920.

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Hartin PJ, Nugent CD, McClean SI, et al. The empowering role of mobile apps in behavior change interventions: The gray matters randomized controlled trial. *JMIR mHealth and uHealth*. 2016;4(3):e93. https://doi.org/10.2196/mhealth.4878.

He Z, Luo Y, Liang G. Runking: A mobile social persuasion system for running exercise. *Proceedings of the Computing, Communications and IT Applications Conference*. 2013;74–78. https://doi.org/10.1109/ComComAp.2013.6533612.

Höchsmann C, Infanger D, Klenk C, Königstein K, Walz SP, Schmidt-Trucksäss A. Effectiveness of a behavior change technique-based smartphone game to improve intrinsic motivation and physical activity adherence in patients with type 2 diabetes: Randomized controlled trial. *JMIR Serious Games*. 2019;7(1):e11444. https://doi.org/10.2196/11444.

Kim B, Lee D, Min A, et al. PuzzleWalk: A theory-driven iterative design inquiry of a mobile game for promoting physical activity in adults with autism spectrum disorder. *PLoS One*. 2020;15(9):e0237966. https://doi.org/10.1371/journal.pone.0237966.

Mansart C, Sukitphittayanon S, Pantongkhum P, Thaicharoen S. Go run go: An Android game-story application for aiding motivation to exercise. *Proceedings of the IEEE International Symposium on Multimedia*. 2016;407–410. https://doi.org/10.1109/ISM.2015.49.

Ryan J, Edney S, Maher C. Engagement, compliance and retention with a gamified online social networking physical activity intervention. *Transl Behav Med*. 2017;7(4):702–708. https://doi.org/10.1007/s13142-017-0499-8.

Schafer H, Bachner J, Pretscher S, Groh G, Demetriou Y. Study on motivating physical activity in children with personalized gamified feedback. *Proceedings of the 26th Conference on User Modeling, Adaptation and Personalization*. 2018;221–226. https://doi.org/10.1145/3213586.3225227.

Shake MC, Crandall KJ, Mathews RP, Falls DG, Dispennette AK. Efficacy of Bingocize®: A game-centered mobile application to improve physical and cognitive performance in older adults. *Games Health J*. 2018;7(4):253–261. https://doi.org/10.1089/g4h.2017.0139.

Steinert A, Buchem I, Merceron A, Kreutel J, Haesner M. A wearable-enhanced fitness program for older adults, combining fitness trackers and gamification elements: The pilot study fMOOC@Home. *Sport Sciences for Health*. 2018;14(2):275–282. https://doi.org/10.1007/s11332-017-0424-z.

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Weber J, Azad M, Riggs W, Cherry CR. The convergence of smartphone apps, gamification and competition to increase cycling. *Transp Res Part F Traffic Psychol Behav*. 2018;56:333–343. https://doi.org/10.1016/j.trf.2018.04.025.

Wong CCK, Kwok RCW. The effect of gamified mHealth app on exercise motivation and physical activity. *Proceedings of the Pacific Asia Conference on Information Systems*. 2016;389.

Study design (n=33):

- No intervention study was conducted (i.e., no RCT or at least a controlled pre-to-post comparison) (n=26)
- No intervention-dependent outcome of interest could be assessed, because no intervention was designed (n=7)

Abraham O, Thakur T, Brown R. Developing a theory-driven serious game to promote prescription opioid safety among adolescents: Mixed methods study. *JMIR Serious Games*. 2020;8(3):e18207. https://doi.org/10.2196/18207.

Alazba A, Al-Khalifa H, AlSobayel H. A proposed game for promoting physical activities among people with low back pain using virtual reality. *Proceedings of the 11th Pervasive Technologies Related to Assistive Environments Conference*. 2018;141–144. https://doi.org/10.1145/3197768.3197780.

Almonani E, Husain W, San OY, Almomani A, Al-Betar M. Mobile game approach to prevent childhood obesity using persuasive technology. *Proceedings of the International Conference on Computer and Information Sciences*. 2014;1–5. https://doi.org/10.1109/ICCOINS.2014.6868418.

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Buttussi F, Chittaro L. Smarter phones for healthier lifestyles: An adaptive fitness game. *IEEE Pervasive Computing*. 2010;9(4):51–57. https://doi.org/10.1109/MPRV.2010.52.

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Chen PL, Saleh W, Pai CW. Pokemon gaming causes pedestrians to run a red light: An observational study of crossing behaviors at a signalised intersection in Taipei City. *Transp Res Part F Traffic Psychol Behav*. 2018;55:380–388. https://doi.org/10.1016/j.trf.2018.03.011.

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Esmaeilzadeh P. The influence of gamification and information technology identity on postadoption behaviors of health and fitness app users: Empirical study in the United States. *JMIR Serious Games*. 2021;9(3):e28282.

Ferreira C, Guimarães V, Santos A, Sousa I. Gamification of stroke rehabilitation exercises using a smartphone. *Proceedings of the 8th International Conference on Pervasive Computing Technologies for Healthcare*. 2014;282–285. https://doi.org/10.4108/icst.pervasivehealth.2014.255326.

Hamari J, Koivisto J. "Working out for likes": An empirical study on social influence in exercise gamification. *Comput Human Behav*. 2015;50:333–347. https://doi.org/10.1016/j.chb.2015.04.018.

Hamaya R, Fukuda H, Takebayashi M, et al. Effects of an mHealth app (Kencom) with integrated functions for healthy lifestyles on physical activity levels and cardiovascular risk biomarkers: Observational study of 12,602 users. *J Med Internet Res*. 2021;23(4):e21622. https://doi.org/10.2196/21622.

Hashim HL, Kamaruddin A, Jantan AH. The mobile exergames design model to encourage physical activity for sedentary generation Z. *Proceedings of the 5th International ACM In-Cooperation HCI and UX Conference*. 2019:137–141. https://doi.org/10.1145/3328243.3328260.

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Janko V, Cvetković B, Gradišek A, Luštrek M, Štrumbelj B, Kajtna T. E-Gibalec: Mobile application to monitor and encourage physical activity in schoolchildren.

Journal of Ambient Intelligence and Smart Environments. 2017;9(5):595–609. https://doi.org/10.3233/AIS-170453.

Kaczmarek LD, Misiak M, Behnke M, Dziekan M, Guzik P. The Pikachu effect: Social and health gaming motivations lead to greater benefits of Pokémon Go use. *Comput Human Behav*. 2017;75:356–363. https://doi.org/10.1016/j.chb.2017.05.031.

Keung C, Lee A, Lu S, O'Keefe M. BunnyBolt: A mobile fitness app for youth. *Proceedings of the 12th International Conference on Interaction Design and Children*. 2013. https://doi.org/10.1145/2485760.2485871.

Lee D, Frey G, Cheng A, Shih PC. Puzzle walk: A gamified mobile app to increase physical activity in adults with autism spectrum disorder. *Proceedings of the 10th International Conference on Virtual Worlds and Games for Serious Applications*. 2018. https://doi.org/10.1109/VS-Games.2018.8493439.

Meixner C, Baumann H, Fenger A, Wollesen B. Gamification in health apps to increase physical activity within families. *Proceedings of the International Conference on Wireless and Mobile Computing, Networking and Communications*. 2019;15–20. https://doi.org/10.1109/WiMOB.2019.8923332.

Mokmin NAM, Jamiat N. The effectiveness of a virtual fitness trainer app in motivating and engaging students for fitness activity by applying motor learning theory. *Education and Information Technologies*. 2021;26(2):1847–1864. https://doi.org/10.1007/s10639-020-10337-7.

Nigg CR, Mateo DJ, An J. Pokémon Go may increase physical activity and decrease sedentary behaviors. *Am J Public Health*. 2017;107(1):37–38. https://doi.org/10.2105/AJPH.2016.303532.

Saksono H, Castaneda-Sceppa C, Hoffman J, Morris V, Seif El-Nasr M, Parker AG. Storywell: Designing for family fitness app motivation by using social rewards and reflection. *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 2020;1–13. https://doi.org/10.1145/3313831.3376686.

SanaulHaque M, Jämsä T, Kangas M. A theory-driven system model to promote physical activity in the working environment with a persuasive and gamified application. *Proceedings of the 1st International Workshop on Data-Driven Gamification Design and MindTrek*. 2017;37–44.

Svendsen GB, Søholt Y, Munch-Ellingsen A, Gammon D, Schürmann A. The importance of being useful and fun: Factors influencing intention to use a mobile system motivating for physical activity. *Proceedings of the 42nd Hawaii International Conference on System Sciences*. 2009;1–10. https://doi.org/10.1109/HICSS.2009.439.

Villasana MV, Pires IM, Sá J, et al. CoviHealth: Novel approach of a mobile application for nutrition and physical activity management for teenagers. *Proceedings of the 5th EAI International Conference on Smart Objects and Technologies for Social Good*. 2019;261–266.

https://doi.org/10.1145/3342428.3342657.

Wattanapisit A, Saengow U, Ng CJ, Thanamee S, Kaewruang N. Gaming behavior with Pokemon GO and physical activity: A preliminary study with medical students in Thailand. *PLoS One*. 2018;13(6):e0199813. https://doi.org/10.1371/journal.pone.0199813.

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APPENDIX 2. KAPPA STATISTIC FOR THE INITIAL AGREEMENT ON FULL-TEXT ELIGIBILITY

The Kappa statistic was reported as the interrater reliability of the 2 reviewers during the full-text screening, according to the Cochrane handbook chapter 7.2.6. Kappa scores of 0.4–0.6, 0.6–0.75, and over 0.75 represent fair, good, and excellent agreement, respectively.

We utilized an online Kappa calculator (https://idostatistics.com/cohen-kappa-free-calculator/) with the following judgements:

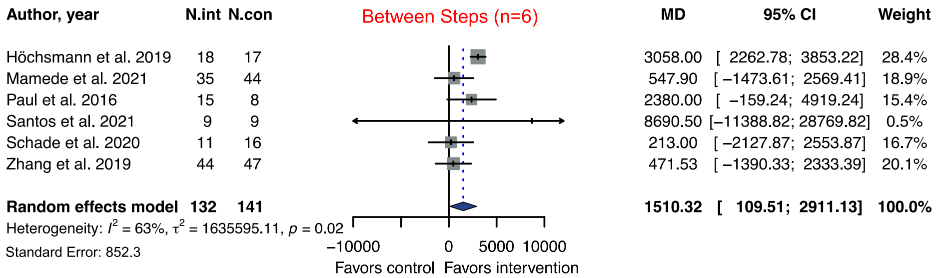
- Both reviewers agreed to include (n=16);
- Both reviewers agreed to exclude (n=75);
- Only the first reviewer wanted to include (n=4);
- Only the second reviewer wanted to include (n=7).

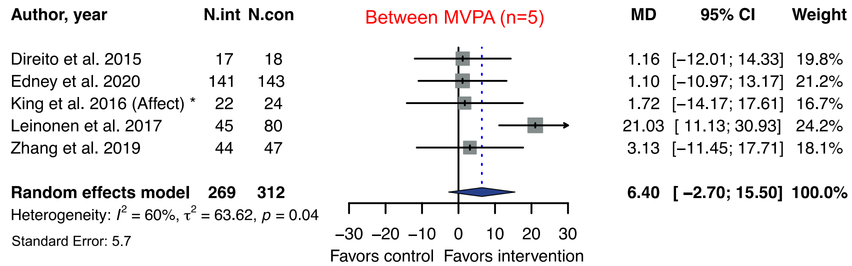
Accordingly, the judgements yielded a Kappa score of **0.68** (good agreement).

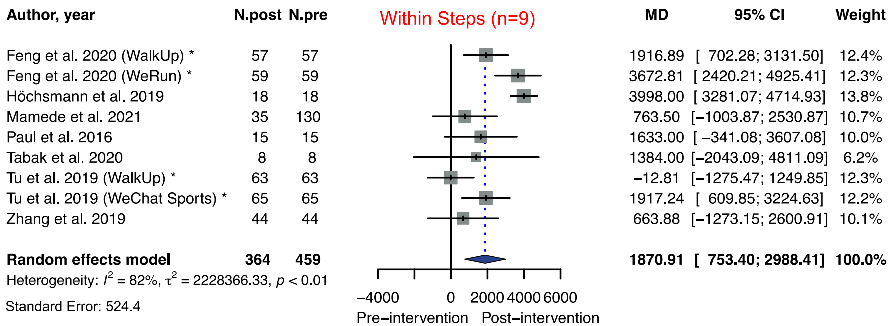
Reasons for Disagreement:
For both reviewers, the uncertainty about inclusion or exclusion was mainly based on the intervention of the studies (PICOS). In particular, they were unsure about whether the intervention of the study could be considered as “standalone” (reviewer 1, n=1; reviewer 2, n=4) or not. Also, they were unsure about the outcomes of physical activity (e.g., studies measured physical activity via questionnaires but focused on behavioral intentions instead of actual physical activity). The disagreement was solved by discussion until reaching consensus (n=19 studies were finally included).

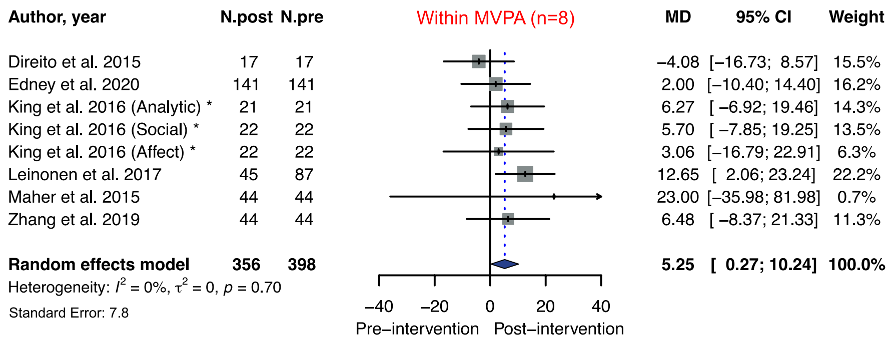
APPENDIX 3. CONVERTING AND RE-EXPRESSING THE SMDS WITH ORIGINAL UNITS (MD) FOR MVPA AND STEP COUNTS

Step 1. Conduct meta-analyses for moderate-to-vigorous physical activity (MVPA, minutes/day) and step counts (steps/day) with the mean difference (MD) method, based on studies with the same units of measure only. The SEs (figure below) of the effect size were obtained.









Step 2. Use the above SEs to calculate the pooled SDs of the effect size for the above studies:

- SD (between-group steps) = SE / sqrt(1 / N.int + 1 / N.con) = 852.3 / sqrt(1/132 + 1/141) = 7037.3
- SD (between-group MVPA) = SE / sqrt(1 / N.int + 1 / N.con) = 5.7 / sqrt(1/269 + 1/312) = 68.5
- SD (Within-group steps) = SE / sqrt(1 / N.post + 1 / N.pre) = 542.4 / sqrt(1/364 + 1/459) = 7471.7
- SD (Within-group MVPA) = SE / sqrt(1 / N.post + 1 / N.pre) = 7.8 / sqrt(1/356 + 1/398) = 106.9

Step 3. Use the above SDs, along with the standardized mean differences (SMDs) from the main meta-analysis (between-group: SMD=0.34 [95% CI=0.06, 0.62]; within-group: SMD=0.38 [95% CI=0.17, 0.59], Figure 3), to extrapolate the mean differences in the main meta-analyses (Figure 3).

- Mean difference (between-group steps) = SMD * SD = 0.34*7037.3 = **2392.7** (95% CI 422.2 to 4363.1) (**→ extrapolate an increase of 2392.7 steps/day**)
- Mean difference (between-group MVPA) = SMD * SD = 0.34*68.5 = **23.3** (95% CI 4.1 to 42.5) (**→ extrapolate an MVPA increase of 23.3 minutes/day**)
- Mean difference (Within-group steps) = SMD * SD = 0.38*7471.7 = **2839.2** (95% CI 1270.2 to 4408.3) (**→ extrapolate an increase of 2839.2 steps/day**)
- Mean difference (Within-group MVPA) = SMD * SD = 0.38*106.9 = **40.6** (95% CI 18.2 to 63.1) (**→ extrapolate an MVPA increase of 40.6 minutes/day**)

Note: The results are exploratory, because the extrapolation is based on the studies with same measurement units only (i.e., step counts: steps/day; MVPA: minutes/day). For step counts, only 6 out of 12 studies (n=12 apps, Figure 3) for between-group studies and 9 out of 12 studies for within-group studies could be used for the analysis. For MVPA, only 5 out of 18 studies (n=18 apps, Figure 3) for between-group studies and 8 out of 18 studies for within-group studies could be used in the analysis.

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Cochrane handbook chapter 12.6.4

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APPENDIX 4. JUSTIFICATION OF DEVIATIONS FROM THE PROTOCOL

Published protocol: PROSPERO CRD42020209502

1. Review Questions
Due to the criticism related to the classification of studies into immersion-, achievement-, and social interaction-related types, this review eliminated the third research question in the protocol ("What types of gamified apps or gamification affordances are potentially more effective?").

2. Search Strategy
The current review considers the grey literature by searching the reference lists of relevant articles (as described in Figure 1). In addition, deviating from the protocol, relevant journals (e.g., JMIR) were not considered as additional sources, because they were indexed in the databases that we searched. We are not aware of a relevant journal that we might have missed. Lastly, although we conceptually distinguished between gamification, game, and game-based, all terms were used as keywords to increase the coverage of potentially included articles.

3. Interventions
The interventions in the current review are further restricted to standalone gamified apps (i.e., without additional supervision or support) or exclusive app use (i.e., without additional intervention types), to assess the effects of purely app-based interventions.

4. Review Team Members
The research assistant (second author of the review, H.H.) was not involved at the time of the protocol registration.

Appendix Table 1. Search Strategy.

1A. Combined three groups of keywords.

Domains	Keywords	References
Gamification	game OR “game-based” OR “game-themed” OR “game-like” OR gamif* OR gamification OR gameful*	[1–6]
Smartphone app	“mobile phone” OR smartphone* OR mHealth OR app OR apps OR “mobile app*” OR “smartphone app*”	[7–9]
Physical activity	exercise* OR sport* OR fitness OR “physical activit*” OR “leisure activit*” OR “physical inactiv*” OR walk* OR step* OR pedomet* OR acceleromet* OR sedentary OR sitting	[10,11]

1B. Databases-specific search strategy.

Database	Results [a]	Search strategy
PubMed	330: (284+46)	((“Games, Recreational”[Mesh]) OR game OR “game-based” OR “game-themed” OR “game-like” OR gamif* OR gamification OR gameful*) AND ((“Mobile Applications”[Mesh]) OR “mobile phone” OR smartphone* OR mHealth OR app OR apps OR “mobile app*” OR “smartphone app*”) AND (((“Exercise”[Mesh]) OR (“Sports”[Mesh]) OR (“Exercise Therapy”[Mesh])OR exercis* OR sport* OR fitness OR “physical activit*” OR “leisure activit*” OR “physical inactiv*” OR walk* OR step* OR pedomet* OR acceleromet* OR sedentary OR sitting)) Filters: English, from 2008 - 2021
Scopus	1103: (998+105)	TITLE-ABS-KEY(game OR “game-based” OR “game-themed” OR “game-like” OR gamif* OR gamification OR gameful*) AND TITLE-ABS-KEY(“mobile phone” OR smartphone* OR mHealth OR app OR apps OR “mobile app*” OR “smartphone app*”) AND TITLE-ABS-KEY(exercise* OR sport* OR fitness OR “physical activit*” OR “leisure activit*” OR “physical inactiv*” OR walk* OR step* OR pedomet* OR acceleromet* OR sedentary OR sitting) AND PUBYEAR > 2008 AND LANGUAGE (English) Filters: limited to journal and conference proceedings
Web of Science	770: (696+74)	TS = (game OR “game-based” OR “game-themed” OR “game-like” OR gamif* OR gamification OR gameful*) AND TS = (“mobile phone” OR smartphone* OR mHealth OR app

		OR apps OR “mobile app*” OR “smartphone app*”) AND TS = (exercise* OR sport* OR fitness OR “physical activit*” OR “leisure activit*” OR “physical inactiv*” OR walk* OR step* OR pedomet* OR acceleromet* OR sedentary OR sitting) AND LANGUAGE: (English) Indexes=SCI-EXPANDED, SSCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, CCR-EXPANDED, IC Timespan=2008-2021; Filters: limited to journal and conference proceedings
PsycINFO	165: (149+16)	(game OR “game-based” OR “game-themed” OR “game-like” OR gamif* OR gamification OR gameful*).mp AND (“mobile phone” OR smartphone* OR mHealth OR app OR apps OR “mobile app*” OR “smartphone app*”).mp AND (exercise* OR sport* OR fitness OR “physical activit*” OR “leisure activit*” OR “physical inactiv*” OR walk* OR step* OR pedomet* OR acceleromet* OR sedentary OR sitting).mp [mp=title, abstract, heading word, table of contents, key concepts, original title, tests & measures; Filters: English, from 2008 - 2021]
ACM Digital Library	179: (158+21)	(game OR “game-based” OR “game-themed” OR “game-like” OR gamif* OR gamification OR gameful*) AND (“mobile phone” OR smartphone* OR mHealth OR app OR apps OR “mobile app*” OR “smartphone app*”) AND (exercise* OR sport* OR fitness OR “physical activit*” OR “leisure activit*” OR “physical inactiv*” OR walk* OR step* OR pedomet* OR acceleromet* OR sedentary OR sitting) [Title (hits = 4+1), Keyword (hits = 11+3), and Abstract (hits = 142+17) were searched separately and then finally combined (hits = 158+21)]

[a]The final search results are the combination of the initial search date (until December 20, 2020) and the updated search date (until August 31, 2021).

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Appendix Table 2. Characteristics of Included Studies (n=19).

Source (country, in which study took place)	Design	Participants; Mean age (range [years])	*N*; Female %; BMI mean [kg/m^2]	App name (OS)	Interventio n arm	Control arm	Duration (week)	PA measure	PA outcome	Risk of bias
Direito et al., 2015 (New Zealand)	RCT	Young adults; 15.66 (14–17)	35; 60; 23.3	Zombies, Run! 5K Training (both)[a]	Immersive app use	Usual behavior	8	Actigraph GT1M[b]; PAQ-A	LPA (min/day); MPA (min/day); VPA (min/day); MVPA (min/day); SED (min/day); PAQ-A	Low
Edney et al., 2020 (Australia)	RCT	Adults; 41.79 (18–65)	284; 75; 29.94	Active Team (both)	Gamified app use	Waitlist control	12	GENEActiv[b]; Active Australia Survey (8 items)	MVPA (min/day)	Some concerns
Feng et al., 2020 (China)	RCT	Undergraduates; NA (18–34)	116; 43.1; Normal	WalkUp; WeRun (both)[a]	WalkUp use	WeRun use	5	Smartphone built-in	Steps/day	Some concerns
Garde et al., 2015 (Canada)	RCT	Children;10.24 (8–13)	47; 66; 70% normal	MobileKids Monster Manor (IOS)[a]	Gamified app use	Daily activity feedback	1	Tractivity monitor	Steps/day	Some concerns
Gremaud et al., 2018 (U.S.)	RCT	Healthy office workers; 40.45 (21–65)	144; 76.4; 29.7	MapTrek (web-app)	MapTrek app + Fitbit use	Use of Fitbit only	10	Fitbit Zip	Active min/day; Steps/day	Some concerns
Haque et al., 2020 (Finland, England, Ireland, Bangladesh)	RCT	Office workers; 39 (24–49)	27; 52; 24.72	iGO (Android)	iGO app use	Paper diary	4	Self-developed, unvalidated single item	Perceived PA increase	High
Höchsmann et al., 2019 (Switzerland)	RCT	Inactive and overweight T2D patients; 58.5 (45–70)	35; 47; 32	MOBIGAME (NA)	Gamified app use	Lifestyle counseling	24	Garmin Vivofit 2	Steps/day	Some concerns
King et al., 2016 (U.S.)	RCT	Underactive adults; 59.5 (>45)	89; 66.7; 29.7	Analytic; Social; Affect (Android)	Use of 3 framed apps	Use of diet-tracker app (Calorific)	8	Smartphone built-in	MVPA (min/day); SED (h/day)	High
Leinonen et al., 2017 (Finland)	RCT	Young men; 17.85 (NA)	354; 0; 23.1	MOPOrtal (web-app)	Gamified app use	Active control, no feedback	24	Polar Active	MVPA (min/day)	Some concerns
Maher et al., 2015 (Australia)	RCT	Healthy adults; 35.6 (18–65)	98; 74.5; 42% normal	Active Team via Facebook app (both)	Gamified app use	Waitlist control	8	Active Australia Survey (8 items)	MPA (min/week); VPA (min/week); Overall PA (min/week); Walking (min/week)	Some concerns
Mamede et al., 2021 (The Netherlands)	RCT	Office workers; 46.8 (>18)	246; 62; 26.3	SelfCarePro app (both)[a]	Gamified app use	Basic version app	5	Fitbit Flex; SQUASH (10 items) and	Steps/day; LPA (h/week); MVPA (h/week); SED (h/week)	Some concerns

								sedentariness (2 items)		
Paul et al., 2016 (Scotland)	RCT	Adult stroke patients; 55.95 (NA)	23; 52; 24.34	STARFISH (Android)	Gamified app use	Usual care	6	ActivPAL[b]	SED (h/day); Steps/day; Walking (h/day)	Some concerns
Santos et al., 2021 (Japan)	RCT	Healthy older Adults; 63.4 (>50)	18; 77.8; NA	Shinpo (Android)	Gamified app use (with social interaction features)	No social interaction	4	Smartphone built-in	Steps/week	Some concerns
Schade et al., 2020 (U.S.)	RCT	Healthy undergraduates; 20.97 (>18)	27; 48; 27.4	Pokemon Go (both)[a]	PG-playing group participation	Non-players	2	Fitbit Charge HR	Steps day; distance traveled/day	Some concerns
Tabak et al., 2020 (The Netherlands)	Single-arm	Older adults; 71 (65–75)	20; 50; NA	WordFit (NA)	Gamified app use	NA	3	FitBit	Steps/day	Moderate [c]
Tu et al., 2019 (China)	RCT	Undergraduates; 21.7 (19–24)	128; 67; Normal	WalkUp; WeChat Sports (both)[a]	WalkUp use	WeChat Sports use	7	Smartphone built-in	Steps/day	Some concerns
Wong et al., 2020 (China)	Single-arm	Children; 10.38 (6–15)	67; 15.38; NA	Family Move (NA)	Gamified app use	NA	8	ActivPAL[b]; IPAQ-SF	MVPA (h/week); MET-minutes/week	Moderate [c]
Zhang et al., 2019 (U.S.)	RCT	African American women; 26.8 (18–35)	91; 100; 31.6	PennFit (Android)	App-Based small group participation	Individual active control	12	FitBit	Steps/day	Low
Zuckerman & Gal-Oz, 2014 (Israel)	RCT	Undergraduates; 23.39 (20–27)	59; 75; NA	StepByStep (Android)	Use of points version vs leaderboard version	Use of quantified version (for monitoring)	1.4	Smartphone built-in	Walking (min/week)	Some concerns

[a]The app is commercially available, otherwise self-designed.
[b]Physical activity was measured by accelerometers designed for research purposes.
[c]Risk of bias was assessed by ROBIS-I, otherwise by RoB-2.

IPAQ-SF, The International Physical Activity Questionnaire-Short Form; LPA, light physical activity; MPA, moderate physical activity; MVPA, moderate-to-vigorous physical activity; OS, operation system of smartphone (Android, IOS, or both); PA, physical activity; PAQ-A, Physical Activity Questionnaires for Adolescents; SED, sedentary time; SQUASH, Short Questionnaire to Assess Health Enhancing Physical Activity; T2D, type 2 diabetes; VPA, vigorous physical activity; min, minutes; h, hours; NA, not applicable.

Appendix Table 3. Full List of Gamification Features and Associated Behavior Change Techniques.

Study	Gamification features *(leveraging features)*	Description/example of features *(and eventual leveraging features)*	Associated BCTs
Direito et al., 2015	1. Storytelling; 2. Virtual progress visualization; *(Performance stats & feedback; Social networking)*	1. Embed training program with a story: users collect supplies and protect a town from zombies; 2. Tracked and virtually displayed progress throughout the program; *(Virtual self-monitoring and receiving feedback on training; Links to associated websites to interact with other users)*	1. NA; 2. Feedback and monitoring; *(Feedback and monitoring; Social support)*
Edney et al., 2020	1. Badges & achievements; 2. Virtual teams & cooperation; 3. Virtual competition; 4. In-game rewards; 5. Virtual Challenges; *(Goal setting; Social networking; Reminders & notifications)*	1. Unlock badges for reaching PA goals; 2. Teammates participating the study together; 3. Compete for highest PA; 4. Virtual gifts for reaching PA goals; 5. Implementation of mini challenges that encourage bursts of PA; *(State predefined goal of daily step count; Post photographs and messages on a Facebook-style newsfeed; Weekly email and push notification)*	1. Imaginary reward; 2. Social support; 3. Comparison of behavior; 4. Imaginary reward; 5. Goals and planning; *(Goals and planning; Social support; Prompts/cues)*
Feng et al., 2020 (WalkUp)[a]	1. Points & scores; 2. Badges & achievements; 3. Levels; 4. In-game rewards	1. Earn points according to walking performances; 2. Earn a badge if the requirement of daily 5,000 step counts are met; 3. Advancement to the next (higher) levels according to walking performances; 4. Earn digital rewards according to walking performances	1. Imaginary reward; 2. Imaginary reward; 3. Imaginary reward; 4. Imaginary reward

Feng et al., 2020 (WeRun) *	1. Leaderboards & rankings; *(Peer-rating; Social networking)*	1. See friends' ranking via WeChat; *(Get likes from friends; Personal profile integrated with friends' profiles as part of the social media platform WeChat)*	1. Comparison of behavior; *(Social reward; Social support)*
Garde et al., 2015	1. Leaderboards & rankings; 2. Virtual competition; 3. Badges & achievements; 4. Virtual progress visualization; 5. Levels; 6. In-game rewards; 7. Storytelling; 8. Virtual teams & cooperation; 9. Virtual Challenges; *(Real world interaction)*	1. Team members see the team's relative standing on the team leaderboard; 2. Competition on which team collectively accumulates the most gold; 3. Achievement of milestones; 4. Countdown on progress toward player's activity goal; 5. Advancement to the next (higher) levels; 6. Rewards of currency and rare items; a player builds a collection of virtual goods, including monsters, furnishing, and pets; 7. Unlocking all of the hidden monsters in 4 multilevel mansions; 8. Encouraging teammates and seeing the team ranking; 9. Creating a complete collection of monsters and manors; *(Real-world physical activity thereby generates gaming currency)*	1. Comparison of behavior; 2. Comparison of behavior; 3. Imaginary reward; 4. Feedback and monitoring; 5. Imaginary reward; 6. Imaginary reward; 7. NA; 8. Social support; 9. Goals and planning; *(NA)*
Gremaud et al., 2018	1. Leaderboards & rankings; 2. Virtual competition; 3. Virtual progress visualization; 4. In-game rewards; 5. Avatar; 6. Virtual teams & cooperation; 7. Virtual Challenges;	1. Race leaderboard; 2. Virtual walking races; 3. Seeing and tracking virtual progress along the route; 4. Reward with a predetermined number of bonus steps (+500 steps); 5. A user's avatar is implemented along the race path; 6. Establishment of competition-based leagues; 7. Step challenges; *(Seeing step achievements; self-monitoring of PA behavior; Seeing real time routes via the Google Street View feature; Daily messages)*	1. Comparison of behavior; 2. Comparison of behavior; 3. Feedback and monitoring; 4. Imaginary reward; 5. NA; 6. Social support;

	(Performance stats & feedback; Real world interaction; Reminders & notifications)		7. Goals and planning; *(Feedback and monitoring; NA; Prompts/cues)*
Haque et al., 2020	1. Leaderboards & rankings; 2. Points & scores; 3. In-game rewards; *(Performance stats & feedback; Reminders & notifications; Social networking)*	1. Monitoring activities on the leaderboard; 2. Every 5 minutes of PA results in 1 point; 3. Reception of progress-related rewards; *(Automated feedback; Receiving notifications; Connection with colleagues for the purpose of PA)*	1. Comparison of behavior; 2. Imaginary reward; 3. Imaginary reward; *(Feedback and monitoring; Prompts/cues; Social support)*
Höchsmann et al., 2019	1. Avatar; 2. In-game rewards; 3. Storytelling; *(Goal setting)*	1. Restoration of a garden, used as a metaphor for one's own body (as avatar); 2. Implementation of appealing in-game rewards for doing PA; 3. Taming of the Schweinehund and restoration of a garden; *(Meeting in-game personalized PA goals)*	1. NA; 2. Imaginary reward; 3. NA; *(Goals and planning)*
King et al., 2016 (Analytic)[a]	1. Levels; *(Performance stats & feedback; Goal setting)*	1. History of prior PA is displayed graphically at individual and group level; *(Numerical feedback, problem-solving information and advice; User-specific goal-setting occurring weekly)*	1. Imaginary reward; *(Feedback and monitoring; Goals and planning)*
King et al., 2016 (Social)[a]	1. Leaderboards & rankings; 2. Virtual teams & cooperation; *(Social networking)*	1. Implementation of live wallpaper; 2. Implementation of virtual group and confederates; *(Message board to share messages with others)*	1. Comparison of behavior; 2. Social support; *(Social support)*

King et al., 2016 (Affect)[a]	1. Badges & achievements; 2. Increasing difficulty; 3. In-game rewards; 4. Avatar; *(Real world interaction)*	1. Bird is happy after 30 min of MVPA; 2. Once the participant surpasses daily levels, additional levels are accessible; 3. Giving person a thumbs-up while making a melodious sound; 4. Use of avatars in the form of a bird; *(Larger jackpot-type reinforcers for extended vocalizations and unexpected arrivals of the bird were provided at different real-world locations)*	1. Imaginary reward; 2. Repetition and substitution (graded tasks); 3. Imaginary reward; 4. NA; *(NA)*
Leinonen et al., 2017	1. Leaderboards & rankings; 2. Virtual competition; 3. Points & scores; 4. Storytelling; 5. Virtual teams & cooperation; 6. Virtual Challenges; *(Performance stats & feedback; Real world interaction; Reminders & notifications)*	1. Personal ranks and team ranks; 2. Implementation of tasks to be solved and combats with another team; 3. Points can be earned based on PA activity; 4. Visual appearance clan game, youth cultures, and conquering; 5. Working together to reach goals to conquer areas; 6. Random new tasks that need to be solved; *(Feedback on PA and sitting time; Track location with GPS; Automated tailored information on health, exercise, and PA instructions)*	1. Comparison of behavior; 2. Comparison of behavior; 3. Imaginary reward; 4. NA; 5. Social support; 6. Goals and planning; *(Feedback and monitoring; NA; Prompts/cues)*
Maher et al., 2015	1. Leaderboards & rankings; 2. Virtual progress visualization; 3. In-game rewards; 4. Virtual teams & cooperation *(Goal setting; Reminders & notifications; Social networking)*	1. Implementation of team tally boards; 2. Implementation of dashboards for progress; 3. Awards for individual and team step-logging and step-count achievements, named by a comedian; virtual gifts such as a high five and a pink leotard; 4. Teams of 3 to 8 existing Facebook friends *(Setting small achievable goals (daily step count); Instructions, daily tips by comedian; Team message board, sending virtual gifts to teammates)*	1. Comparison of behavior; 2. Feedback and monitoring; 3. Imaginary reward; 4. Social support *(Goals and planning;*

			Prompts/cues; Social support)
Mamede et al., 2021	1. Leaderboards & rankings; 2. Points & scores; 3. Increasing difficulty; 4. Virtual teams & cooperation; 5. In-game rewards; 6. Storytelling; 7. Avatar; *(Real world interaction; Goal setting; Reminders & notifications; Performance stats & feedback)*	1. A leaderboard serves for intrateam cooperation and competition between teams; 2. Earning points by team or individuals; 3. Challenges start easy and become increasingly more difficult; 4. Virtual teams; 5. Rewarding participants with virtual awards for both individuals and team achievements; 6. Virtual walking tour (e.g., a roundtrip across Rotterdam); 7. Virtual avatars crossing the virtual tour scenarios; *(Charity representations sponsored by the municipality; Virtual walking tour as a goal to achieve, goal setting starting from 8500 steps; Biweekly newsletters during the challenges; Weekly personalized feedback on step count progress)*	1. Comparison of behavior; 2. Imaginary reward; 3. Graded tasks; 4. Social support; 5. Imaginary reward; 6. NA; 7. NA; *(NA; Goals and planning; Prompts and cues; Feedback and monitoring)*
Paul et al., 2016	1. Leaderboards & rankings; 2. Increasing difficulty; 3. In-game rewards; 4. Avatar; 5. Virtual teams & cooperation; *(Performance stats & feedback; Goal setting)*	1. Participant's fish swims and blows bubbles and others can see; 2. If achieved, the target will increase by 5%; 3. Exclamation mark attached to their fish, fish's fins and tail grows; 4. Each person gets a metaphor by colored fish within a fish tank; 5. There are 4 members per group; team rewards for another sea creature; *(Real-time feedback; Individualized step goals, daily step count target)*	1. Comparison of behavior; 2. Graded tasks; 3. Imaginary reward; 4. NA; 5. Social support; *(Feedback and monitoring; Goals and planning)*
Santos et al., 2021	1. Levels; 2. In-game rewards; 3. Avatar;	1. Colors feature 4 levels; advancement to the next (higher) levels 2. One card is received for every unique hotspot and for every 1,000 steps player walked;	1. Imaginary reward; 2. Imaginary reward;

	4. Virtual teams & cooperation; 5. Virtual competition; 6. Points & scores; 7. Storytelling; *(Peer-rating; Real world interaction; Social networking)*	3. Players choose a public avatar and nickname and can make a short self-introduction; 4. Players are randomly assigned to a challenge group; 5. Battling other players within the game; 6. Gaining experience points; 7. Capturing and hatching virtual creatures; *(When players receive cards as the result of other players' actions, they have a chance to give them a like; Players must collect virtual cards by visiting shrines and temples in Kyoto city; Leaving gifts to other people)*	3. NA; 4. Social support; 5. Comparison of behavior; 6. Imaginary reward; 7. NA; *(Social reward; NA; Social support)*
Schade et al., 2020	1. Avatar; 2. Points & scores; 3. Virtual competition; 4. Levels; *(Social networking)*	1. Users can walk indoors and outdoors to capture and hatch virtual creatures; 2. Users can gain experience points; 3. Users can battle other players within the game; 4. Users with high physical activity can increase levels within the game; *(Social and exploration aspects to increase the adherence)*	1. NA; 2. Imaginary reward; 3. Comparison of behavior; 4. Imaginary reward; *(Social support)*
Tabak et al., 2020	1. Leaderboards & rankings; 2. Badges & achievements; 3. Increasing difficulty; 4. In-game rewards; 5. Storytelling; 6. Virtual Challenges; *(Performance stats & feedback; Personalization; Social networking)*	1. Achievements are present through leaderboards; 2. Elements enabling achievement; 3. Implementation of difficulty levels; 4. Improved activity behavior enhances rewards, unobtrusive rewarding (hammers); 5. Obtaining as many hammers as possible to finish puzzles, with 3 themes: Forest-lake, Snow-mountain, and Rocks-coast; 6. Solving and creating challenges, providing challenges to unlock themes; *(In-game statistics; Unique playing boards; Sharing with other users, social accounts [buddy, guest])*	1. Comparison of behavior; 2. Imaginary reward; 3. Graded tasks; 4. Imaginary reward; 5. NA; 6. Goals and planning; *(Feedback and monitoring; NA; Social support)*

Tu et al., 2019 (WalkUp)[a]	1. Points & scores; 2. Badges & achievements; 3. Levels; 4. In-game rewards	1. Energy points: value of energy required to travel around the virtual world; 2. Travel badges: visa to countries across seven continents; 11 types of walking achievements (e.g., reach a certain number of steps/day); 3. Levels of progression: advancement to the next (higher) levels depending on the number of steps taken; 4. Virtual supplement: virtual goods that can speed up users' walking progress	1. Imaginary reward 2. Imaginary reward 3. Imaginary reward 4. Imaginary reward
Tu et al., 2019 (WeChat Sports)[a]	1. Leaderboards & rankings; 2. Virtual teams & cooperation; *(Peer-rating)*	1. Ranking based the number of step-counts per day; 2. Users can add friends to a team; *(Likes: users can like the walking performance of their friends in the WeChat social network)*	1. Comparison of behavior; 2. Social support; *(Social reward)*
Wong et al., 2020	1. Points & scores; 2. In-game rewards; *(Performance stats & feedback; Reminders & notifications; Social networking)*	1. Points system and simple exercise scoreboard; 2. Gift redemption; *(Personal record/performance; Push notifications: text messages; Joyful interactions between two people)*	1. Imaginary reward; 2. Imaginary reward; *(Feedback and monitoring; Prompts/cues; Social support)*
Zhang et al., 2019	1. Leaderboards & rankings; 2. Virtual progress visualization; 3. Virtual teams & cooperation; *(Social networking)*	1. Seeing one's PA and other 3 group members' PA; 2. App homepage displays all 4 women's PA data in form of colored bars in real time; 3. Four members per group; *(Sending messages to their group through an instant chatting tool, allowing for individual profiles)*	1. Comparison of behavior; 2. Feedback and monitoring; 3. Social support; *(Social support)*
Zuckerman & Gal-Oz.,	1. Points & scores; *(Performance stats & feedback; Goal setting)*	1. Implementation of a point-collecting tool; *(Continuous measurement and real-time feedback; Goal-setting of a 10% increase of daily walking)*	1. Imaginary reward;

2014 (Points)[a]			*(Feedback and monitoring; Goals and planning)*
Zuckerman & Gal-Oz., 2014 (Leaderboard)[a]	1. Leaderboards & rankings	1. Installment of a real-time leaderboard ranking users	1. Comparison of behavior

[a]The manuscripts contained 2 or 3 different gamified apps. Separate analyses were made for these different apps.

BCT, behavior change technique; GPS, global positioning system; MVPA, moderate-to-vigorous physical activity; NA, not applicable; PA, physical activity.

Appendix Table 4. Risk of Bias of the Included Studies (n=19).

Study	**Randomization process**	**Deviations from intended interventions**	**Missing outcome data**	**Measurement of the outcome**	**Selection of the reported result**	**-**	**-**	**Overall bias**
RoB-2								
Direito et al., 2015	Low	Low	Low	Low	Low	-	-	Low
Edney et al., 2020	Low	Low	Low	Some concerns	Low	-	-	Some concerns
Feng et al., 2020	Low	Low	Low	Some concerns	Some concerns	-	-	Some concerns
Garde et al., 2015	Low	Low	Low	Low	Some concerns	-	-	Some concerns
Gremaud et al., 2018	Low	Some concerns	Low	Low	Low	-	-	Some concerns
Haque et al., 2020	Low	Some concerns	Low	High	Low	-	-	High
Höchsmann et al., 2019	Low	Low	Some concerns	Low	Low	-	-	Some concerns
King et al., 2016	Low	Low	High	Low	Low	-	-	High
Leinonen et al., 2017	Low	Low	Some concerns	Low	Low	-	-	Some concerns
Maher et al., 2015	Low	Some concerns	Low	Low	Low	-	-	Some concerns
Mamede et al., 2021	Low	Some concerns	Low	Low	Low	-	-	Some concerns
Paul et al., 2016	Some concerns	Some concerns	Low	Some concerns	Low	-	-	Some concerns
Santos et al., 2021	Low	Some concerns	Low	Low	Low	-	-	Some concerns
Schade et al., 2020	Low	Low	Some concerns	Low	Low	-	-	Some concerns
Tu et al., 2019	Low	Low	Low	Some concerns	Some concerns	-	-	Some concerns
Zhang et al., 2019	Low	Low	Low	Low	Low	-	-	Low
Zuckerman & Gal-Oz, 2014	Some concerns	Some concerns	Low	Low	Low	-	-	Some concerns
-	**Bias due to confounding**	**Bias in selection of participants into the study**	**Bias in classification of interventions**	**Bias due to deviations from intended interventions**	**Bias due to missing data**	**Bias in measurement of outcomes**	**Bias in selection of the reported result**	**Overall bias**
ROBINS-I								
Tabak et al., 2020	Critical	Low	Low	Moderate	Low	Low	Low	Moderate
Wong et al., 2020	Low	Low	Low	Moderate	Low	Moderate	Low	Moderate

RoB, risk of bias; ROBINS-I, Risk of Bias In Non-randomized Studies - of Interventions.

Appendix Table 5. Sensitivity Analyses.

Sensitivity analysis	Studies	SMD (95% CI)	I^2 %	*p*-value
Between-group				
Leave-one-out[a]	11	0.20 (0.02, 0.38)	31.0	0.030
Remove studies with high overall risk of bias	11	0.37 (0.07, 0.68)	74.2	0.016
Risk of bias: over 4 categories as low	10	0.33 (0.01, 0.64)	76.0	0.042
Risk of bias: less than 4 categories as low	2	0.44 (–0.08, 0.96)	0.0	0.095
Within-group				
Leave-one-out[a]	17	0.30 (0.15, 0.45)	47.8	<0.001
Remove studies with high overall risk of bias[b]	15	0.42 (0.18, 0.66)	78.3	0.0007
Risk of bias: over 4 categories as low	13	0.31 (0.06, 0.56)	71.4	0.015
Risk of bias: less than 4 categories as low	5	0.53 (0.17, 0.90)	75.0	0.004

[a]Leave one study out due to high heterogeneity (Höchsmann et al., 2019).
[b]There were 2 studies with high overall risk of bias (Haque et al., 2020; King et al., 2016).

SMD, standardized mean difference.

Appendix Table 6. Assessment of Level of Evidence with GRADE Guidelines.

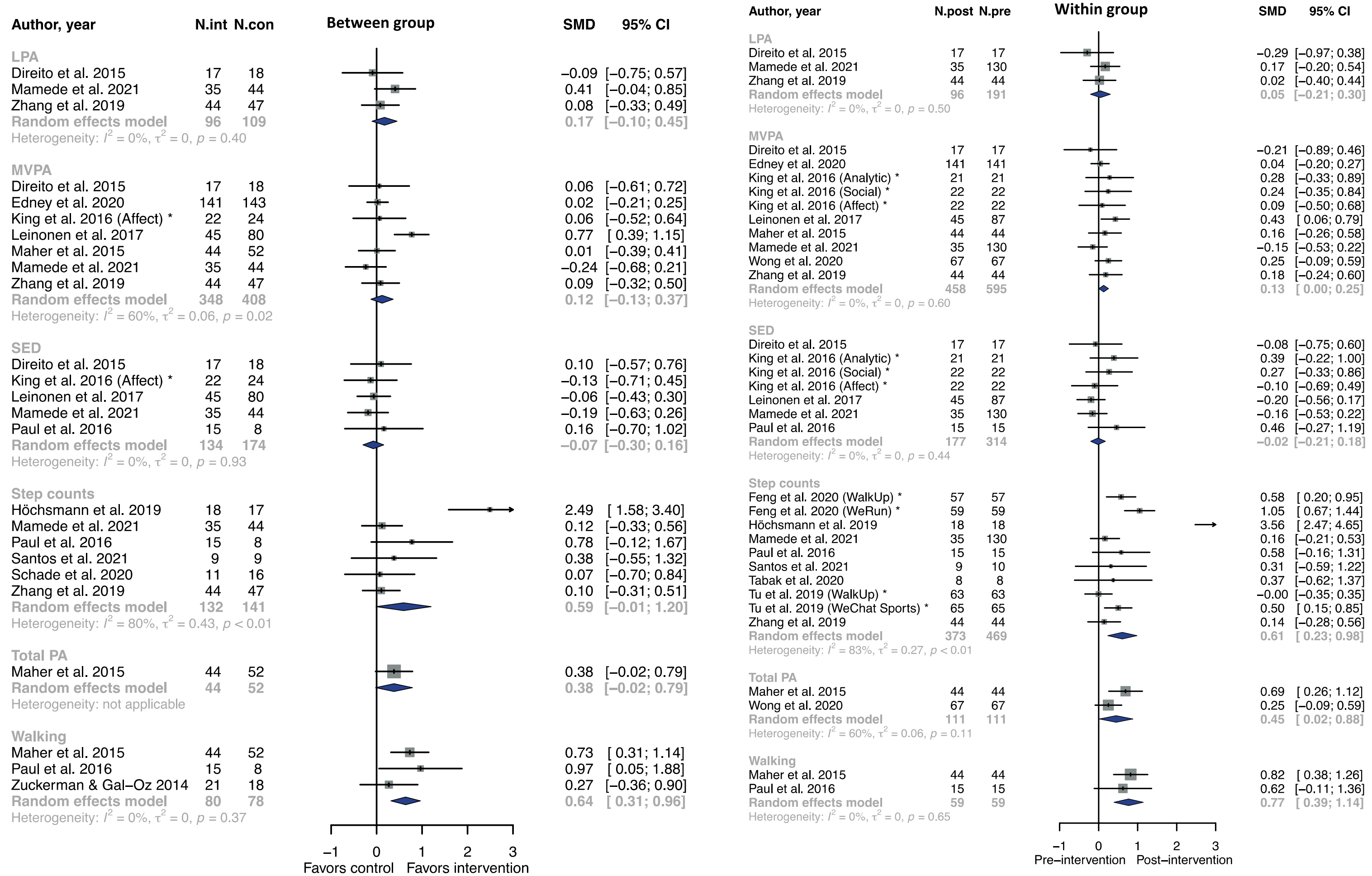
Certainty assessment							Summary of findings	
	Participants (studies)	**Risk of bias**	**Inconsistency**	**Indirectness**	**Imprecision**	**Publication bias**	**Overall certainty of evidence**	**SMD (95% CI)**
Between group (RCTs)								
Main effects	898 (12)	not serious	serious [a]	not serious	not serious	none	⊕⊕⊕◯ Moderate	0.34 (0.06, 0.62)
LPA	205 (3)	not serious	not serious	not serious	serious [b]	none	⊕⊕⊕◯ Moderate	0.17 (–0.10, 0.45)
MVPA	756 (7)	not serious	serious [a]	not serious	not serious	none	⊕⊕⊕◯ Moderate	0.12 (–0.13, 0.37)
SED	308 (5)	not serious	not serious	not serious	serious [b]	none	⊕⊕⊕◯ Moderate	–0.07 (–0.30, 0.16)
Step counts	273 (6)	not serious	serious [a]	not serious	serious [b]	none	⊕⊕◯◯ Low	0.59 (–0.01, 1.20)
Total PA	96 (1)	not serious	not serious	not serious	serious [b]	none	⊕⊕⊕◯ Moderate	0.38 (–0.02, 0.79)
Walking	158 (3)	not serious	not serious	not serious	serious [b]	none	⊕⊕⊕◯ Moderate	0.64 (0.31, 0.96)
Within group (Single-armed pre-to-post interventions)								
Main effects	1642 (18)	not serious	serious [a]	not serious	not serious	none	⊕◯◯◯ Very Low	0.38 (0.17, 0.59)
LPA	287 (3)	not serious	not serious	not serious	serious [b]	none	⊕◯◯◯ Very Low	0.05 (–0.21, 0.30)
MVPA	1053 (10)	not serious	serious [a]	not serious	not serious	none	⊕◯◯◯ Very Low	0.13 (0.00, 0.25)
SED	491 (7)	not serious	not serious	not serious	not serious	none	⊕⊕◯◯ Low	–0.02 (–0.21, 0.18)
Step counts	842 (10)	not serious	serious [a]	not serious	not serious	none	⊕◯◯◯ Very Low	0.61 (0.23, 0.98)
Total PA	134 (2)	not serious	serious [a]	not serious	serious [b]	none	⊕◯◯◯ Very Low	0.45 (0.02, 0.88)
Walking	118 (2)	not serious	not serious	not serious	serious [b]	none	⊕◯◯◯ Very Low	0.77 (0.39, 1.14)

[a]Downgrade due to I^2 statistics >50%.

[b]Downgrade due to pooled sample sizes <400. The GRADE level of evidence for within-group (n=18 apps) should be interpreted with caution, because single-armed pre-to-post studies start as low-quality evidence, and 16 out of the 18 included studies (apps) were the intervention groups of RCTs (i.e., there were only 2 observational studies).

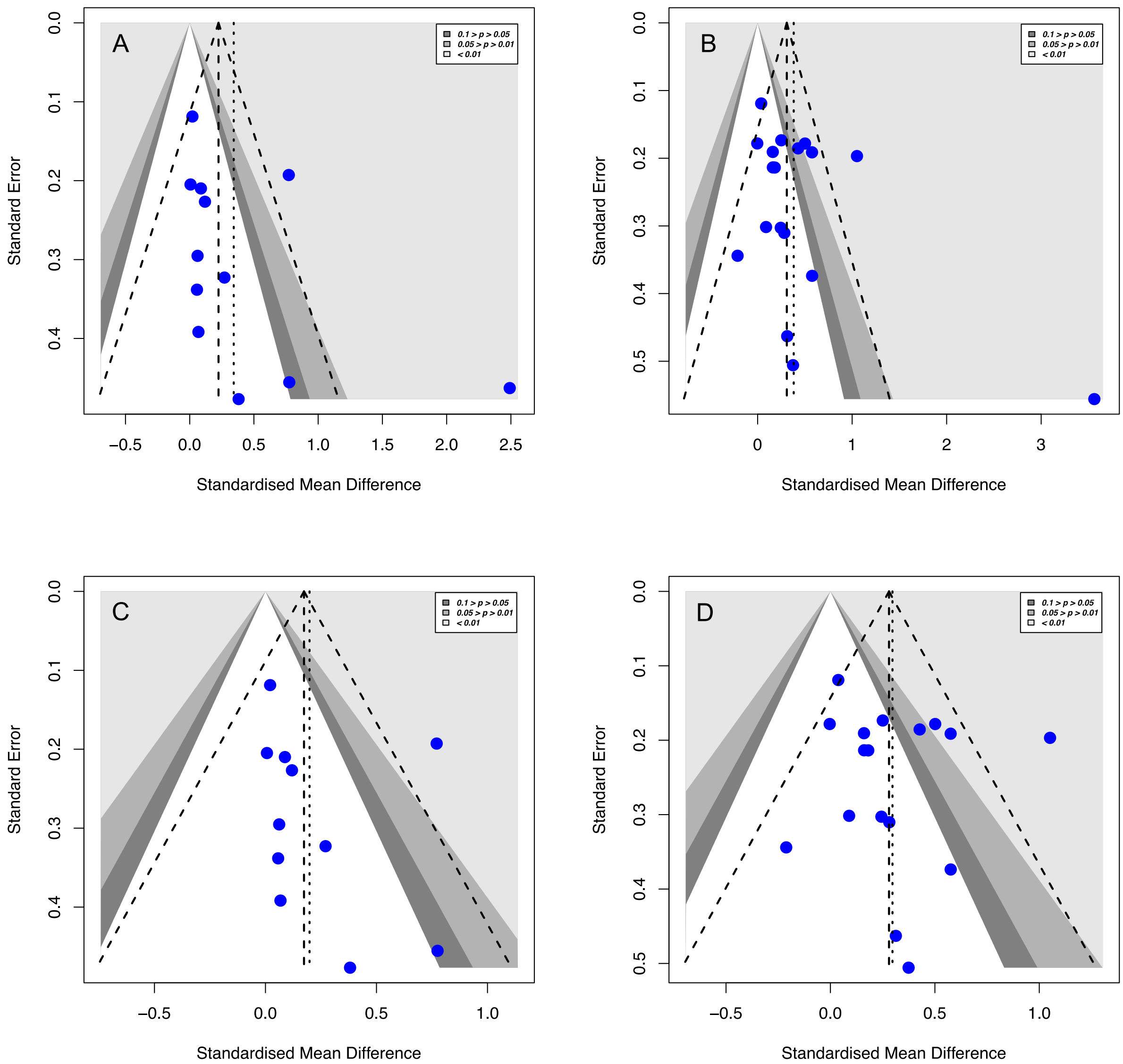
LPA, light physical activity; MVPA, moderate-to-vigorous physical activity; SED, sedentary behavior; SMD, standardized mean difference; GRADE methodology, RCTs start as high-quality evidence, while before-after studies start as low-quality evidence. According to the GRADE handbook, the quality of evidence was downgraded by one level for each of the following issues: (1) risk of bias when >25% of the participants were from studies with a high risk of bias; (2) inconsistency when the I^2 statistic >50%; (3) imprecision when pooled sample sizes <400; (4) publication bias based on testing for funnel plot asymmetry.

Appendix Figure 1. Secondary meta-analysis: Pooled effect sizes for each physical activity outcomes in between-group RCTs and within-group pre-to-post interventions.



Note. Each PA outcome (e.g., MVPA, step counts) was analyzed separately (since a single study may have more than 5 different PA outcomes); thus, no overall pooled SMD can be estimated. LPA, light physical activity; MVPA, moderate-to-vigorous physical activity; SED, sedentary behavior; SMD, standardized mean difference.

Appendix Figure 2. Contour-enhanced funnel plots with Egger's test.



Note. A: Funnel plot for between group (Egger's test: t(df)=1.62 (10), *p*=0.14). B: Funnel plot for within group studies (Egger's test: t(df)=1.61 (16), *p*=0.13). C: Funnel plot for between group studies after leave-one-out sensitivity analysis (Egger's test: t(df)=0.87 (9), *p*=0.41). D: Funnel plot for within group studies after leave-one-out sensitivity analysis (Egger's test: t(df)=0.45 (15), *p*=0.66). *p*>0.05: no publication bias.

Effects of Gamified Smartphone Applications on Physical Activity: A Systematic Review and Meta-Analysis

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