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Paving the Way for Medical AI:
Consumer Response to Artificial Intelligence in Healthcare

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Abstract

Advanced analytics, such as artificial intelligence (AI), have increasingly gained relevance in the medical domain and are gradually changing the landscape of healthcare. Medical AI applications are becoming more pervasive and are even expanding into areas that were previously the territory of human experts. Although much is known about AI's performance, patients' responses to the involvement of AI in the care process remains unclear. This thesis investigates consumers' involvement in the AI value creation process with respect to two aspects: input creation and output validation.

The first aspect encompasses consumers' role as contributors of high-quality data, representing an important input factor for AI. Three empirical studies (Study 1-3) assessed the effects of requests for personal information for AI-based healthcare research purposes – by two healthcare organizations (a university hospital vs. a pharmaceutical company) – on individuals' likelihood to disclose personal information about their health. For the latter, the studies considered two dimensions: the tendency to self-disclose and the tendency to falsify personal information. The results revealed that individuals attributed higher altruistic motives to university hospitals' requests for information, while pharmaceutical companies were perceived as being driven by egoistic motives. Individuals were more willing to disclose data if they perceived that the requesting organization is acting based on altruistic motives (i.e., the motives function as gate openers). Individuals were more likely to protect their data by intending to provide false information when they perceived egoistic motives to be the main driver for the organization requesting their data (i.e., the motives function as a privacy protection tool). Two moderators, namely message appeal (Study 2) and message endorser credibility (Study 3), influence these two indirect pathways of the provision of personal information. The findings add to Communication Privacy

Management Theory as well as Attribution Theory by suggesting motive-based pathways to the release of correct personal health data. Compared to not-for-profit organizations, for-profit organizations are recommended to match their message appeal with the organizations' purposes and to use high-credibility endorsers in order to reduce inherent disadvantages in motive perceptions.

To investigate consumers' role as gatekeepers for AI implementation in health care delivery, a fourth study explored whether individuals were more likely to follow a medical recommendation dependent on the level of AI integration in the diagnostic process. Considering a highly (vs. less) severe disease individuals were more likely to comply with the recommendation of a physician (with or without AI support) compared to a fully automated AI tool that replaced the physician. Two pathways increased the intention to comply with the recommendation. When a physician performs the assessment (vs. automated AI), social presence is high, which increases compliance intentions. When AI performs the assessment (vs. physician only), innovativeness perception is high, which increases compliance intentions. When physicians use AI, perceived innovativeness increases and social presence does not decrease. Pairing AI with a physician in medical diagnosis leads to higher compliance intentions than AI on its own.

Zusammenfassung

Hochentwickelte Analysetools wie künstliche Intelligenz (KI) gewinnen im Bereich der Medizin zunehmend an Bedeutung und verändern allmählich die Gesundheitslandschaft. Medizinische KI-Anwendungen werden immer allgegenwärtiger und verbreiten sich zunehmend in Bereichen, die zuvor auf rein menschlicher Expertise basierten. Obwohl bereits viel über die Leistungsfähigkeit von KI bekannt ist, sind die Reaktionen der Patienten in Hinblick auf die Einbindung von KI in den Pflegeprozess noch unklar. Diese Dissertation untersucht das Mitwirken der Verbraucher am KI-Wertschöpfungsprozess in zwei Aspekten: Generierung von Inputfaktoren und Ergebnisvalidierung.

Der erste Aspekt betrachtet die Rolle der Verbraucher als „Spender" qualitativ hochwertiger Daten, die eine wichtige Grundlage für KI darstellen. Drei empirische Studien (Studie 1-3) untersuchen die Auswirkungen einer Datenanfrage zweier Gesundheitsorganisationen (Universitätsklinikum vs. Pharmaunternehmen) zur Nutzung für KI-basierte Forschungszwecke auf die Bereitschaft von Konsumenten, ihre persönlichen Gesundheitsdaten preiszugeben. Die Studien betrachten zwei Dimensionen der Bereitschaft zur Datenherausgabe: die Neigung zur Offenlegung korrekter Informationen und die Neigung zur Verzerrung bzw. Falsifizierung persönlicher Informationen. Die Ergebnisse zeigten, dass Individuen der Informationsanfrage der Universitätskliniken eher altruistische Motive zuschrieben, während Pharmaunternehmen als von egoistischen Motiven geprägt wahrgenommen wurden. Die Befragten waren eher bereit Daten offenzulegen, wenn sie der Ansicht waren, dass die anfragende Organisation auf Basis altruistischer Motive handelt (d. h. Motive fungieren als Toröffner). Auf der anderen Seite schützen Einzelpersonen ihre Daten, indem sie tendenziell falsche Informationen bereitstellen, sofern sie egoistische Motive als Haupttreiber für die Organisation vermuten, die ihre Daten anfordert (d. h. die Motive fungieren als Instrument zum Schutze der Privatsphäre). Des Weiteren werden diese beiden indirekten Wege der Bereitstellung persönlicher

Informationen von zwei Moderatoren beeinflusst – der Appell der Nachricht (Studie 2) und der Glaubwürdigkeit des Nachrichten-Endorsers (Studie 3). Die Ergebnisse der drei empirischen Studien ergänzen die Theorie des Kommunikationsdatenschutzmanagements sowie die Attributionstheorie, indem sie motivbasierte Wege zur Freigabe korrekter persönlicher Gesundheitsdaten aufzeigen. Im Vergleich zu gemeinnützigen Organisationen wird gewinnorientierten Organisationen empfohlen, den Appell ihrer Nachrichten an die Ziele der Organisationen anzupassen und Personen mit hoher Glaubwürdigkeit einzusetzen, die die Nachricht unterstützen, um die inhärenten Nachteile der Motivwahrnehmung zu verringern.

Um die Rolle der Verbraucher als Weichensteller für die Implementierung von KI im Gesundheitswesen zu betrachten, wurde in einer vierten Studie die Wahrscheinlichkeit untersucht, dass Patienten einer medizinischen Empfehlung folgen (Patientencompliance) in Abhängigkeit vom Grad der Nutzung von KI im Diagnoseprozess. In Anbetracht einer schweren (im Vergleich zu einer weniger schweren) Erkrankung befolgten Personen eher die Empfehlung eines Arztes (mit oder ohne KI-Unterstützung) als die eines vollautomatischen KI-Tools, welches den Arzt vollständig ersetzt. Zwei Pfade verstärkten die Absicht, sich an die Empfehlung zu halten: Wenn ein Arzt (im Vergleich zur automatisierten KI) die Beurteilung durchführt, ist die empfundene soziale Präsenz hoch, was wiederum die Compliance erhöht. Wenn eine KI die Diagnose erstellt (im Vergleich zum Arzt), ist die wahrgenommene Innovationskraft hoch, was ebenfalls die Compliance erhöht. Bei Ärzten, die KI im Diagnoseprozess einsetzen, nimmt die wahrgenommene Innovationskraft zu und die soziale Präsenz nimmt nicht ab. Die Kombination von KI mit einem Arzt in der medizinischen Diagnose führt zu einer höheren Compliance als eine KI allein.

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List of Abbreviations

AI	Artificial Intelligence
e.g.	exempli gratia (for example)
EHR	Electronic Health Record
et al.	et alii (and others)
i.e.	id est (that is)
ns	not significant
vs.	versus
WHO	World Health Organization

1. Introduction

Artificial intelligence (AI) is a highly debated topic in the healthcare environment that has recently re-emerged into scientific and public awareness, as new technological breakthroughs have been published by scientists and technology companies at a rapid pace. Medical AI applications are becoming more pervasive and expanding into areas that were previously the sole territory of human experts such as diagnosing diseases or choosing the right treatment. AI is making the promise to improve healthcare quality by creating social and economic values (Günther et al., 2017). This is based on the premise that AI can reduce medical errors by outperforming expert-level accuracy (Haenssle et al., 2018) and deliver cost-effective healthcare (Esteva et al., 2017). While AI's performance has already been examined deeply (Benjamens et al., 2020; De Fauw et al., 2018; Esteva et al., 2017), little is known about consumers' perceptions of AI applications in healthcare. This thesis aims to assess how consumers respond to and whether they are willing to accept AI for health-related purposes. A better empirical understanding of consumers' responses can provide scholars and practitioners with an insight into the dynamics and nuances of AI's impact as well as practical tools to facilitate adoption processes.

1.1. Motivation and Aim

AI is increasingly considered one of the most important technological innovations for healthcare with tremendous benefits on medical functions (Topol, 2019). The promising value of AI in healthcare has created an increasing interest within academic and business communities throughout many disciplines (Davenport & Kalakota, 2019; Garbuio & Lin, 2019). Nevertheless, a first stream of research on AI's impact and capabilities has mostly focused on addressing technological aspects like performance and accuracy (De Fauw et al., 2018; Esteva et al., 2017). A second stream of literature has discussed the value of AI in providing support to clinicians (Yu et al., 2018) or the economic and strategic gains for healthcare organizations (Raghupathi & Raghupathi, 2014; Wang & Hajli, 2016). Even though there is an increasing call for a more patient-centered, value-based orientation in healthcare delivery (Agarwal et al., 2020; Porter, 2010), research on consumers' interests regarding AI health applications is still scarce. This leaves many consumer-relevant issues unanswered. For example, it is not yet fully understood how consumers respond to AI health applications. Will they accept the use of AI in health-decision-making? What are their preferences for interaction? Which factors facilitate the usage of AI for individuals' health management? Consumers are also the main recipients of AI healthcare products and services, and are consequently the ultimate arbiter on approving AI technology for their health management. AI's success is thus dependent on consumers' receptivity in the direct interaction with AI applications, as well as on consumers' information sharing behavior, which indirectly contributes to its quality. AI health applications are powered by the wealth of consumers' health information. High accuracy and reliability can only be achieved under the premise of high-quality data, which in turn are determined by individuals' willingness to truthfully share their personal health information. Hence, consumer involvement is necessary for the whole AI value creation process.

The goal of this thesis is to address this gap of a lack of consumers' perspectives on AI health applications and investigates how consumers' involvement at different stages in the AI value creation process contributes to the development of high-quality solutions. More precisely, this thesis aims at answering two main research questions:

1) *How do individuals manage the disclosure and protection of their personal health information in response to healthcare organizations' data requests?*
2) *How does the integration of AI into the health service delivery process influence consumers' intentions to comply with medical recommendations?*

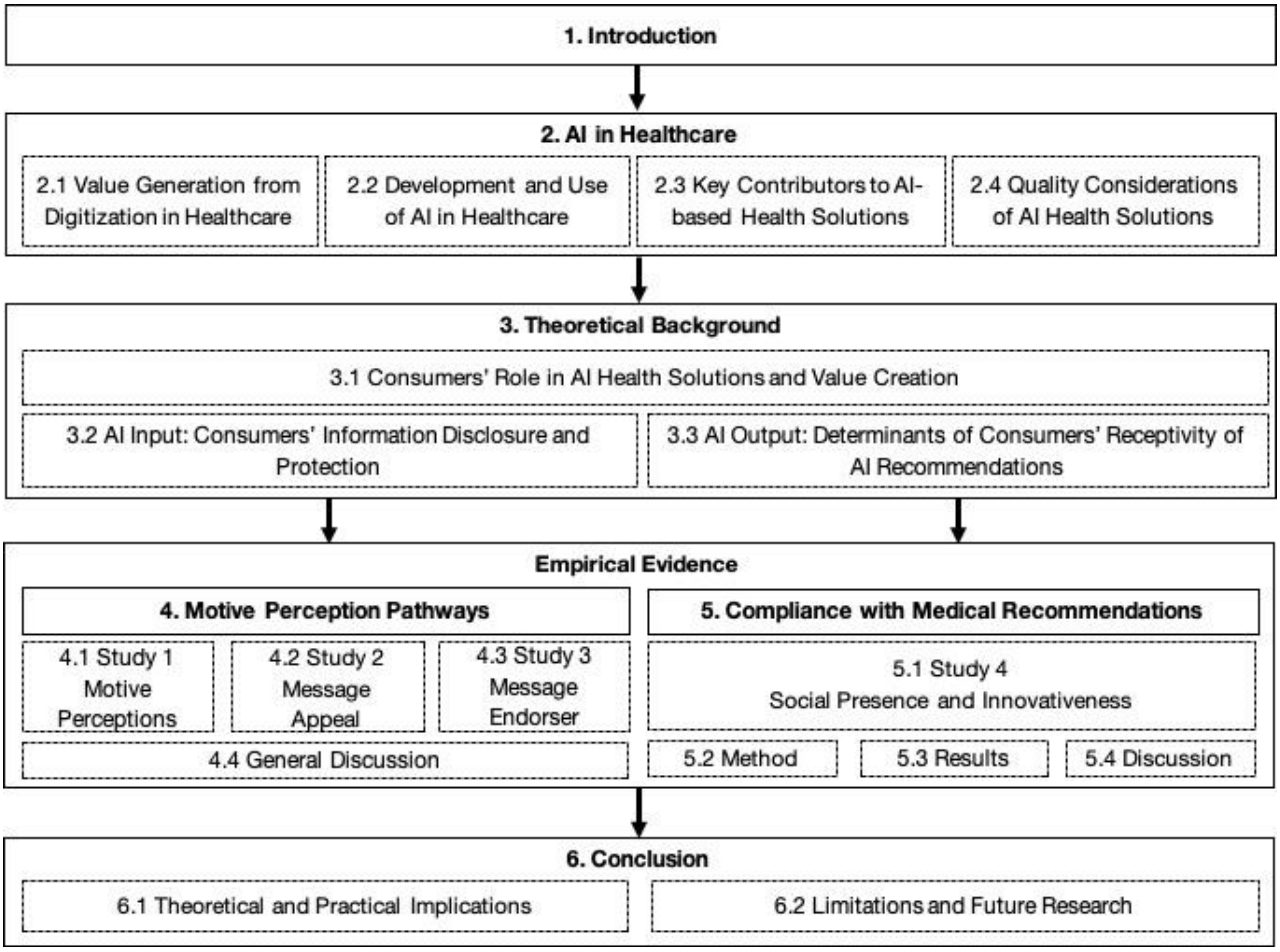
Accordingly, in chapter 4 the first part of this thesis aims to answer research question one by focusing on consumers' intentions to reveal or restrict information in response to the data collection attempts for AI-based research purposes of two different healthcare organizations. The healthcare environment is characterized by multiple stakeholders who are all pursuing different interests and often conflicting goals. In light of a lack of clarity about their goals, consumers are likely to attribute different underlying motives to healthcare organizations in response to a request for information. This thesis examines which motives individuals attribute to not-for-profit compared to for-profit healthcare organizations and how these impact individuals' information sharing intentions. It further tests the effectiveness of different communication tools in persuading consumers to truthfully share information with healthcare organizations. To answer the second research question, the second part of this thesis , in chapter 5, explores the influence of different levels of AI integration in the medical diagnostic process on individuals' compliance intentions.

By addressing these two research questions this thesis makes several contributions. First, it contributes to the research on individuals' information-sharing behavior by introducing attributed motives, a construct known from cause-related marketing research, as a novel factor that has so far not been considered in the research on individuals' information management. Second, this thesis is among the first to take a dual approach in the assessment of individuals' information management by considering self-disclosure as well as misrepresentation intentions. Third, this thesis advances the understanding of consumers' decision to comply with a medical recommendation based on the integration of AI in the medical assessment process.

1.2. Structure of the Thesis

This thesis is structured as follows (see Figure 1). Chapter 1 gives a short introduction to the topic, explains the general objectives of this work and presents the structure of this thesis.

Figure 1 *Structure of the Thesis*



Chapter 2 provides a conceptualization of AI in healthcare and how it creates value, and gives an overview of current applications in the healthcare landscape. Moreover, it introduces the three main contributors to AI value creation that are the focus of this research: data, technology and stakeholders. The last section highlights the relevance of healthcare quality dimensions for the evaluation of AI health applications.

Chapter 3 elaborates on consumers' roles at different levels of AI value creation and introduces the theoretical background that guides the subsequent empirical studies. The first section (chapter 3.1) outlines the relevance of consumers in the AI value creation process in general and describes the different contributions to quality assessment within Donabedian's structure-process-output framework. The following sections each focus on one component of this framework and introduce the respective theoretical background. Building on Communication Privacy Management theory, the second section (chapter 3.2) draws special attention to the role of consumers as information providers, which determines the quality of input for AI value creation. Attribution theory serves as the theoretical basis for the hypothesis investigating consumers' responses to the request for personal health information by two different healthcare organizations. The section further discusses how organizations' persuasion strategies might influence this information request. The last section (chapter 3.3) examines the role of consumers as gatekeepers for AI implementation in the medical decision-making process. First, it illustrates individuals' overall receptivity to medical AI applications. Subsequently, it discusses factors that influence consumers' acceptance of medical recommendations, including the role of the level of AI involvement in the diagnostic process, disease severity, social presence as well as innovativeness.

Chapter 4 encompasses three experimental studies that address the first research question and test the hypotheses proposed in chapter 3.2. Study 1 tests the relationship between the data collection request from two different health organizations and individuals' intentions to reveal or restrict health information. It further investigates the mediating effect of two motive perceptions (egoistic vs. altruistic) that individuals attribute to the healthcare organizations' request. Studies 2 and 3 address the same relationship while considering the message appeal and message endorser as additional contextual factors moderating the relationship. Data for all three studies were gathered via online surveys with US participants.

Chapter 5 aims to answer the second research question and explores the role of disease severity, social presence and innovativeness for consumers' medical decision-making as proposed in chapter 3.3. It presents Study 4 which investigates the relationship between three different diagnostic methods, with varying levels of AI integration, and individuals' intentions to comply with the medical recommendation. Moreover, the study assesses the mediating effects of social presence and innovativeness on the examined relationship. Data were collected via an online survey with US participants. Table 1 gives an overview of the methods used in the four empirical studies presented in chapter 4 and 5.

Table 1 *Overview of Study Characteristics*

	Study 1	**Study 2**	**Study 3**	**Study 4**
Main goal	Assess the effect of healthcare organizations' data request in individuals' information disclosure intentions via attributed motives	Assess the impact of message appeal on the influence of requesting entity on information disclosure via attributed motives	Assess the impact of message endorser on the influence of requesting entity on information disclosure via attributed motives	Explore the impact of AI involvement in the diagnostic process on individuals' compliance intentions via social presence and innovativeness
Design	Experiment; Online survey	Experiment; Online survey	Experiment; Online survey	Experiment; Online survey
Sample	US N = 204	US N = 330	US N = 328	US N = 452
Manipulation	Health data requesting entity	• Health data requesting entity • Message appeal	• Health data requesting entity • Message endorser	• Diagnostic method • Disease severity

	Study 1	Study 2	Study 3	Study 4
Measured constructs	• Self-disclosure intention • Falsification intention • Egoistic and altruistic motives	• Self-disclosure intention • Falsification intention • Egoistic and altruistic motives	• Self-disclosure intention • Falsification intention • Egoistic and altruistic motives	• Compliance intention • Social presence • Innovativeness
Statistical method	Structural equation modeling; Mediation analysis	Structural equation modeling; Moderated-mediation analysis	Structural equation modeling; Moderated-mediation analysis	Regression based mediation analysis

The thesis closes with a general conclusion in chapter 6 outlining the overall findings, discussing theoretical and managerial implications, and suggesting topics for further research.

2. Conceptual Overview: AI in Healthcare

Definition and Conceptualization of AI

AI is a broad subject, associated with a range of similar terms such as 'machine intelligence', 'intelligent agents' and 'algorithms' (Alsheibani et al., 2018). Davenport et al. (2020), referring to the previous definitions in the field, proposed that AI "refers to programs, algorithms, systems, and machines that demonstrate intelligence" (Shankar, 2018, p. vi); AI is "manifested by machines that exhibit aspects of human intelligence" (Huang & Rust, 2018, p. 155), and involves machines mimicking "intelligent human behavior" (Syam & Sharma, 2018, p. 136). Russell and Norvig (2016) highlighted AI's ability to mimic cognitive functions generally associated with human attributes such as learning, speech and problem-solving. The various definitions conform to the same premise: that AI can be labeled as a non-human intelligence that is programmed to perform a task that is normally done by humans (Dwivedi et al., 2019). To perform tasks that typically require human intelligence, AI harnesses theories, algorithms and computing frameworks (Xu et al., 2019). Performing these tasks encompasses various methods and technologies such as machine learning, deep learning, natural language processing, computer vision, physical robots and robotic process automation (Davenport et al., 2020; He et al., 2019; Xu et al., 2019). Based on these technologies, AI is able to interpret and learn from data, and also utilize this learning to be able to swiftly adapt to perform specific tasks (Kaplan & Haenlein, 2019).

Levels of Intelligence of AI

The literature distinguishes between weak or narrow AI and strong or general AI (Baum et al., 2011; Kaplan & Haenlein, 2019; Reese, 2018). Most of the current AI applications are associated with the first category – weak - meaning that these are rather practical applications that are specified for singular, or limited (narrow) tasks (e.g. playing chess) (Dwivedi et al., 2019), and mostly require only a single human capability for execution (Hengstler et al., 2016; Russell & Norvig, 2016). These algorithms only operate in a pre-determined range and cannot perform outside the task that they are designed for. In contrast strong (also specified as general) AI suggests the human-like intelligence of a machine, implying that the system has cognitive capabilities and can understand and process its environment like humans (Dwivedi et al., 2019; Mesko et al., 2018). While both narrow and general AI may equal or even outperform humans, general AI can learn to advance into new domains (Kaplan & Haenlein, 2019).

Based on these two concepts, researchers map AI applications onto different levels of intelligence (Davenport & Kirby, 2016; Huang & Rust, 2018), which describes AI's capacity to learn from experience and adapt to the environment (Sternberg, 2005). Intelligence is a skill formerly attributed primarily to humans. It enables complex cognitive processes such as reasoning, problem-solving, communication or perceiving (Russell & Norvig, 2016). Huang and Rust (2018) distinguished between four types of intelligence: mechanical, analytical, intuitive and emphatic. The first two are associated with the group of narrow AI and the latter with the group of general AI.

The first group includes AI applications with mechanical intelligence, which are systems that are standardized or rule based, and are designed to perform routine, repeated tasks (Huang & Rust, 2018). They are characterized by consistency and logic, which makes them only applicable to contexts with clearly defined rules and predictable outcomes (Davenport et al., 2020). To maintain consistency, they are equipped with limited learning or adaptive abilities (Huang & Rust, 2018). Robots are one example of a mechanical AI application. They are rule based, operate autonomously without needing instructions and cannot adapt automatically; they do not understand their environment and rely on prior knowledge which is updated in an *ad hoc* manner (Huang & Rust, 2018). Humans can perform mechanical processes almost automatically with little or no extra thought. A physician can listen to heartbeats or a check pulse without much cognitive effort (Huang & Rust, 2018), since they have performed the task several times and has internalized the procedure. The focus on consistency in these tasks provides mechanical AI an advantage over humans since machines are not constrained by fatigue or other distractions.

But AI can also perform more difficult analytical tasks involving more sophisticated skills like information processing for problem-solving, logical reasoning or mathematical skills (Sternberg, 1999, 2005). These abilities are gained through training, learning and cognitive thinking. The most common application of analytical intelligence is machine learning. Similar to a psychiatrist analyzing a conversation, machine learning uses algorithms to learn iteratively from data to find insightful information without being programmed to what to look for (SAS Institute Inc.

2017). Despite its seemingly sophisticated intelligent behavior, analytical AI is considered weak AI in the AI literature (Huang & Rust, 2018). Even though it can perform complex tasks, it is not able to simulate intuition and is restricted to systematic, consistent and predictable tasks (Huang & Rust, 2018).

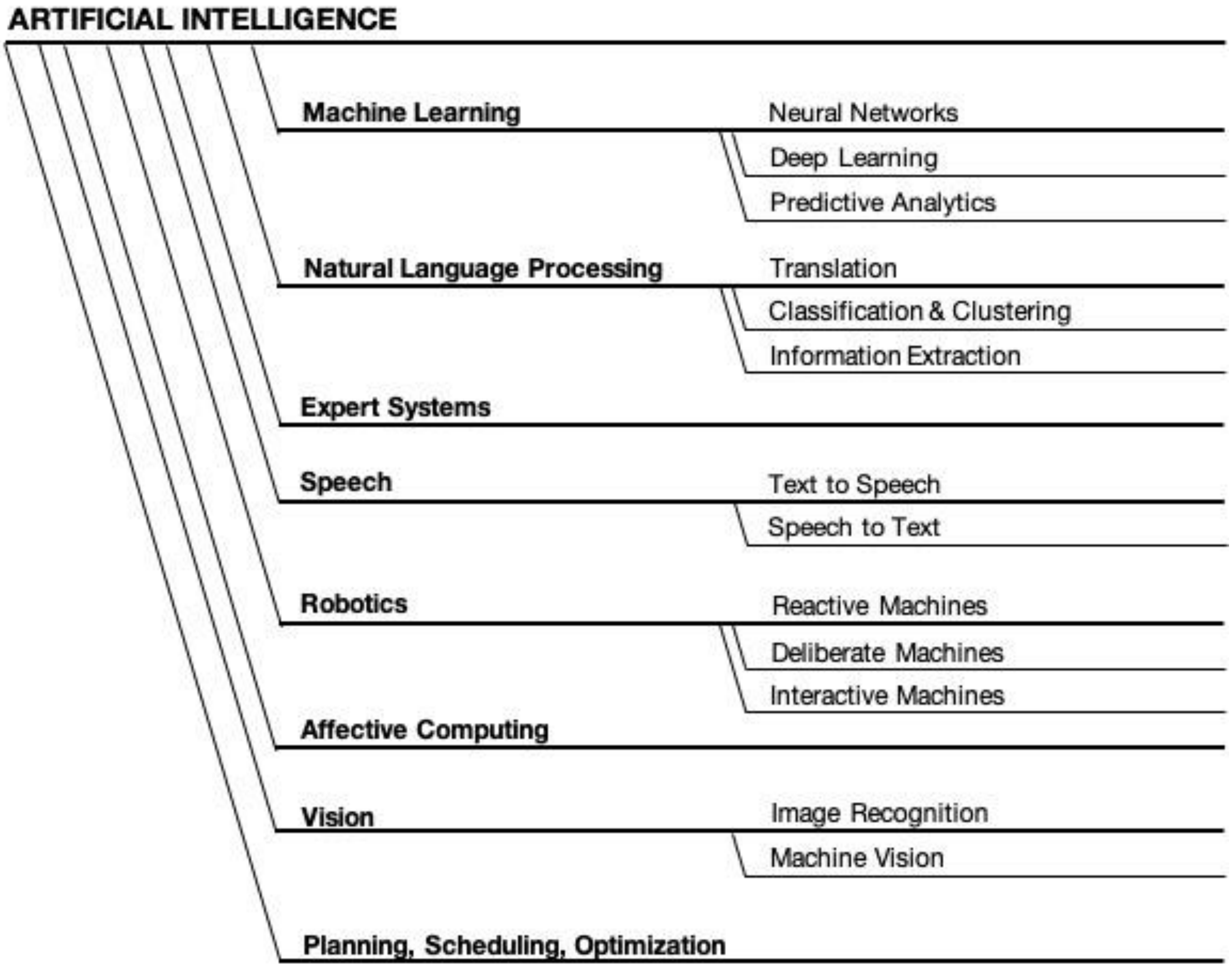
The second group of AI applications associated with general AI includes intuitive and emphatic intelligence, which are designed to function in a more human-like way. Davenport and Kirby termed it context awareness, meaning that machines and algorithms are able to learn and advance beyond their initial programming without human assistance (Davenport et al., 2020). A key characteristic that distinguishes intuitive (strong) intelligence from analytical (weak) AI is understanding. This aspect is still questioned by many that claim machines lack a consciousness, mind or subjective awareness (Azarian, 2016). Intuitive tasks are interactive and relational, which need some level of social presence (Giebelhausen et al., 2014; van Doorn et al., 2016; Wünderlich et al., 2012). A psychiatrist, for example, needs social and emotional skills to understand the symptoms and diagnosis of a patient and to propose an adequate treatment. Intuitive AI mimics the human cognitive capabilities to think creatively and to adapt to novel contexts (Huang & Rust, 2018). AI with emphatic intelligence even goes one step further. It is designed with the ability to recognize and understand peoples' emotions and respond emotionally in an appropriate way (Goleman, 1996). Emphatic AI, also known as affective computing, describes a machine that can (or at least creates the impression that it can) feel, relate to emotions or influence emotions (Picard, 2003) - just as a psychiatrist communicates and empathizes with patients to provide emotional support. The key characteristic of empathetic AI is the ability to experience things (Huang & Rust, 2018). There is much debate about whether AI is capable of experiencing emotions. While some argue that emotions are biological reactions and subjective experiences hard to transform into binary code, others claim that emotions are comparable cognitions and hence can be easily programmed (Huang & Rust, 2018). Davenport et al. (2020) noted that AI is best conceptualized as a continuum of intelligence since some AI applications have already moved beyond task automation but still fall short of context awareness. Independent of these categorizations, many researchers are skeptical that human-like capabilities can be accomplished soon (Müller & Bostrom, 2016). In addition, the ethical, economic and social implications associated with more autonomous and intelligent AI and its wider impact on human life, equality and sustainability, remain highly controversial (Bigman & Gray, 2018; Duan et al., 2019).

Subfields of AI

There are many subfields of AI which include, but are not limited to, neural networks (e.g. deep learning), genetic computing, computer vision (e.g. image recognition, machine vision), robotics, affective computing, natural language processing, and machine learning. Figure 2 provides an overview of the current areas of AI technology. The list is not intended to be exhaustive, but to give an impression of the most common AI technologies existing at present. Many of these already are already being applied in healthcare (see chapter 2.2). These applications can be projected on a reality-virtuality continuum (Milgram et al., 1995). While most of the AI applications are virtual, with or without some elements of physical embodiment, AI can also be embedded in a physical entity or a robot form. Surgical robots that assist physicians in minimally-invasive procedures (Gomes, 2011) or open-heart surgeries combine virtual reality (Khor et al., 2016) with AI embodied in a physical robot. But there are even more humanoid robots that possess different levels of anthropomorphism (van Doorn et al., 2016), such as assistive social agents (Heerink et al., 2008; Heerink et al., 2010) or companion robots (Robinson et al., 2014) used in elderly care.

However, most AI applications, such as virtual nursing assistants or decision support systems that help with diagnostic and treatment decisions, are purely virtual.

Figure 2 *Areas and Application of AI Technology*



Notes: Adapted from Atlam et al. (2018), Murphy (2019)

This thesis focusses on AI as a virtual, analytical tool that can process big data and gain valuable insights to support decision-making. Within this thesis, AI is conceptualized as a tool within big data analytics, meaning that data are collected throughout the healthcare system and subsequently processed by algorithms, which are then used to make (data-driven) decisions based on relationships identified in the data (Newell & Marabelli, 2015). The roles of AI in human decision-making can be broadly classified as support/assistance or replacement (Edwards et al., 2000). With the development of more advanced machines, it is now possible for AI to perform more complex tasks using cognitive capabilities which are traditionally only attributed to humans, such as making tacit judgments, sensing emotion or driving processes (Mahroof, 2019). In light of increasing autonomy, such systems run without much human oversight (Zlotowski et al., 2017). Among the benefits of AI decision-making is its ability to reach improved decision quality, boost humans' analytical skills and decision-making abilities, and heighten creativity (Wilson & Daugherty, 2018). Equipped with these skills, it is worthwhile to prove AI's value for the healthcare system. The following section introduces the specifications of value creation in healthcare and how AI can contribute to better care.

2.1. Value Generation from Digitization in Healthcare

What is Value Creation in Healthcare?

The term 'value creation' comprises two aspects; it refers to the process and the content of the new creation. The process describes how value is generated while content is the result of this process and determines what is valuable for the receiver (Lepak et al., 2007). Bowman and Ambrosini (2000) classified the content of value creation as use-value. Use-value describes the subjective judgment of users who ascribe value to a specific quality of a new product based on their needs. Therefore, value depends on the relative amount of benefits subjectively perceived by a user. This idea is closely related to the concept of customer value, which Woodruff (1997) defined as "a customer's perceived preference for, and evaluation of, those product attributes, attribute performances, and consequences arising from use that facilitates (or blocks) achieving the customer's goals and purposes in use situations" (Woodruff, 1997, p. 142).

Value creation processes can be performed by individuals, organizations or society. Value is created by developing novel tasks, processes, products or services, using new methods or technologies. Lepak et al. (2007) summarized: "The value creation process includes any activity that provides a greater level of novel and appropriate benefits than the target user or customer currently possesses, and that they are willing to pay for" (Lepak et al., 2007, p. 184).

According to Porter (2010), the primary goal of healthcare delivery is the creation of high value for patients, which he defines as "the health outcomes achieved per dollar spent" (Porter, 2010, p. 2477). He claimed that the deficiencies in the health system can be ascribed to the fact that value remains largely unmeasured and misunderstood. He further argued that value creation in the healthcare system centers on minimizing short-term costs and not on addressing results, meaning the improvement of a patient's medical condition over the full care cycle (Porter & Teisberg, 2006). Accordingly, care delivery should focus on customer needs and create value by the promotion of wellness and treatment of illnesses (Agarwal et al., 2020). In the current system, consumers only play a minor role in the healthcare ecosystem. Although they drive the demand for health services and are the final users, care delivery is primarily shaped by providers, suppliers and payers (Agarwal et al., 2020). This yields undesirable outcomes for patients, such as the unintended over-provision of services (Porter & Kaplan, 2016) or products (e.g. marketing of opioids) (Hadland et al., 2018; Hadland et al., 2019). Even though cost is part of the value equation, the challenge is the proper measurement of the outcomes achieved (Porter, 2010). But one of the most widely used quality measurement systems is the Healthcare Effectiveness Data and Information Set (HEDIS), which almost entirely focuses on the assessment of care processes but not outcomes (National Committe for Quality Assurance, 2020). Given the limited attention to consumer value in healthcare and the absence of proper value measurements, there is an increasing demand for a shift toward a more value-based care system (Burwell, 2015). To specify patient-centered value creation and measurement Agarwal et al. (2020) proposed three dimensions of value: preferences, precision and process (see Table 2).

Table 2 *Three P's of Patient-Centered Value Creation in Healthcare*

Dimension	Preferences	Precision	Process
Definition	Identifying what matters to consumers and providing them with the resources to make informed choices congruent with their needs and values	Addressing consumer health needs with precision, which requires not only promoting wellness and treating illnesses effectively but also doing so in ways tailored to consumers' predisposition	Adopting a consumer-oriented culture to maximize satisfaction and minimize burdens on consumers
Status-quo	Consideration and integration of preferences are limited by challenges in dynamically assessing preferences and providing personalized decision-making tools	Focus on average treatment effects and a system that cannot easily implement interventions targeted to consumer needs	Lack of transparency and poor communication create information gaps and other inconveniences for patients
Examples for Patient-centered care	• Measuring the weight that a patient assigns to the dimension of care outcomes • Providing patients with personalized risk assessments based on data from similar patients	• Matching patients' genomic profile with drugs to minimize the risk • Motivating desirable patient behavior using remote interventions based on patients' psychological profile	• Providing patients with mobile access to physicians' clinical notes • Using remote monitoring devices to reduce need for in person consultation

Notes: Adapted from Agarwal et al. (2020)

Value Creation, Big Data Analytics and AI

Recent technological advances facilitate the shift from volume-based to value-based care. Value-based care capitalizes increasingly on the emergence of health analytics as a tool to quantify outcomes and deliver value (Agarwal et al., 2010; Bates et al., 2014). To create value for patients, many applications are developed that address different challenges embedded in the whole care cycle. In 2018 the World Health Organization (WHO) released a classification of Digital Health Interventions (DHI) which should be used in tandem with the list of Health System Challenges (HSC) to articulate how technology is addressing identified health needs (World Health Organization, 2018a). Technological applications should target the improvement of the following eight categories of HSC: 1) information, 2) availability, 3) quality, 4) acceptability, 5) utilization, 6) efficiency, 7) cost and 8) accountability. It further specified different target groups that need to be addressed by the digital functionalities of health interventions including clients/users of health services, healthcare providers, health system/resource managers and data services that support a wide range of activities.

The availability of massive volumes of healthcare data, as well as the rise of advanced technologies such as AI and machine learning with their powerful analytical capabilities, makes it possible to develop solutions that are targeted to their patients' needs. The utilization of analytical capabilities creates superior value by leveraging data in innovative ways and revealing hidden insights into health data (Saggi & Jain, 2018). Leveraging predictive analytics capabilities and their speed for decision-making can improve the quality and efficiency of care (Fernandes et al., 2012; Kruse et al., 2016). By using data on patients' unique characteristics, algorithms generate a set of predictions about the effectiveness of various treatment options or identify patients who need extra follow-up (Wang & Hajli, 2016). Their optimization modeling capability is used to define the best decision from various options (Saggi & Jain, 2018), while also considering real-time resource utilization productivity thus improving efficiencies and the quality of care (Jee & Kim, 2013). Consequently, opportunities to reduce healthcare challenges are substantial.

One of the major challenges in healthcare are diverse and dispersed data. Thanks to technological advancements, this problem now becomes solvable. A relevant benefit of advanced analytics tools is that they can integrate heterogeneous data, which are typically fragmented in multiple health systems and devices, to create new knowledge (Mohr et al., 2013). Furthermore, it can process a large amount of data in only a few seconds which shortens the time of decision-making and permits proactive treatment before patients' conditions worsen (Wang & Hajli, 2016). The automatization of highly repetitive tasks releases the costly capacity of health workers for more complex tasks. Monitoring and analyzing real-time medical data saves costs by identifying unknown patterns related to readmission or unnecessary tests and treatments (Mohr et al., 2013; Wang & Hajli, 2016). Finally, the implementation of advanced analytical tools brings significant improvements to patients through patient-centric care and personalized medicine. Their capabilities to analyze and integrate various data (e.g. genomics) with medical records helps translate personalized medicine into clinical practice (Chawla & Davis, 2013; Jensen et al., 2012). This not only enables a personalized patient-specific record of disease risks (Mohr et al., 2013) but also allows patients to make better-informed decisions and thus empowers them to play a more active role in their care (Baker et al., 2014).

2.2. Development and Use of AI in Healthcare

There are many deficits and challenges in current healthcare systems such as diagnostic errors (Singh et al., 2014), high costs, inefficiencies in workflow, inequitable distribution of care delivery (Kruk et al., 2018) and waste of resources (Berwick & Hackbarth, 2012). To address these deficiencies there is a growing need for new technologies, which help to understand the complexities of the healthcare system and provide the necessary productivity gains to enable a more efficient care delivery and a more value-based system (Ward et al., 2014). The increasing availability of healthcare data and rapid development of analytical methods catalyzed the emergence of AI healthcare applications (Jiang et al., 2017). By discovering associations and understanding patterns and trends within the data they can extract new insights that support healthcare providers and other stakeholders in the healthcare system to make better-informed decisions (Raghupathi & Raghupathi, 2014).

Even though the integration of AI in the healthcare landscape is just beginning, it already shows an impact on various levels of the healthcare system. Healthcare actors involved in the interaction with AI applications encompass any individual or organizations that provides, controls, accepts or supports the healthcare service (Mantzana et al., 2017). The following section discusses the relevance of AI using the example of the following health actors: clinicians, hospitals, insurances, research institutes, patients and health authorities.

AI for Clinicians. AI applications span many disciplines such as radiology, pathology, dermatology, ophthalmology, gastroenterology, cardiology, oncology or mental health. The main application of AI for clinicians is in the form of pattern recognition using deep neural networks that can help interpret medical images. Medical images are an important source for diagnosis, therapy assessment, and planning, prognosis and screening (Belle et al., 2015). Some examples in clinical settings are medical scans, pathology slides, skin lesions, retinal images, EKG or vital signs (Topol, 2019). Usually, the results of AI image interpretation are compared with the assessments of medical experts. Levels of accuracy are indicated by the so-called Area Under the Curve (AUC), which measures the area of a plot of true-positive vs. false-positive rates (Topol, 2019). While unlikely to replace human healthcare providers entirely, AI can perform certain tasks with greater consistency, speed and reproductivity (He et al., 2019). Various disciplines assessed the accuracy of algorithms in diagnosing or classifying diseases against medical experts. Studies in radiology showed that algorithms were much faster (Titano et al., 2018) and more accurate than radiologists in interpreting medical scans (Nam et al., 2019). AI recently led to remarkable improvements in the diagnosis of wrist fractures, a difficult diagnostic task for physicians in emergency rooms. It was able to increase sensitivity from 81% to 92% and to reduce the rate of misinterpretation by 47% (Lindsey et al., 2018). Houssami et al. (2017) also highlighted the potential of AI in reducing human detection errors like false positives in breast cancer screening. A study testing the accuracy of algorithms in the classification of breast cancer from digital pathology slides showed that the synergy from combined pathologist and AI interpretations led to the best accuracies (Steiner et al., 2018). Besides diagnosis and classification tasks in radiology and pathology, a deep learning-algorithm proposed urgent referral of patients with various retinal pathologies. The algorithm did not miss a single urgent referral case, while experts only agreed on 65% of referral decisions (De Fauw et al., 2018). Another study in the field of ophthalmology suggests that the application of deep neural networks on retinal images can also transcend the diagnosis of eye disease and be applied for the early diagnosis of dementia (Mutlu et al., 2018), or cardiovascular risk factors (Poplin et al., 2018). AI has also been explored to support battling the enormous burden of mental health. Various tools have been developed to lend support to clinicians by predicting successful antidepressant medication (Chekroud et al., 2016), characterizing depression (Reece & Danforth, 2017; Schnyer et al., 2017), predicting suicide (Just et al., 2017; Walsh et al., 2017) and identifying bouts of psychosis in schizophrenics (Chung et al., 2018).

However, researchers argue that accuracy should not be the sole performance indicator for algorithms since it does not imply clinical efficacy (Keane & Topol, 2018). The outcome of an algorithm with an AUC of .99 might be highly accurate, but it remains pointless unless it demonstrates improved clinical outcomes in real-world settings (Keane & Topol, 2018). One major limitation of studies on AI applications is their reliance on in-silico data (Coudray et al., 2018; Mori et al., 2018). Synthetic data, as well as a general lack of large datasets with carefully labeled data, narrow the validation for real-world settings.

AI for Hospitals. AI's capability to predict key outcomes is also highly relevant in clinical settings to provide more efficient and precise care. Using data from Electronic Health Records (EHR), machine learning and deep learning algorithms estimate the risk of patients' hospital readmission and mortality rates (Rajkomar et al., 2018; Shameer et al., 2017). Furthermore, AI predictive tools can estimate the risk of adverse events, such as the development of sepsis or septic shock (Hao, 2020). In one study, the recommendations for medication and dosage for patients with sepsis by an AI tool were on average reliable and more effective than treatments chosen by humans (Komorowski et al., 2018). With the help of machine vision, which uses data from sensors in the clinical setting, patient safety can be improved by monitoring. Analysis of real-time data from critical patients in intensive care units provides actionable insights and can significantly reduce reaction-time for decision-making (Suresh et al., 2017). Besides the prediction of key outcomes and safety issues in the clinical setting, AI increases productivity in workflows and reduces inefficiencies in care delivery. It can be applied to tasks such as image interpretation or the scheduling of operation theaters or clinical appointments, which are highly repetitive and labor- and time-intensive. This not only addresses shortages in the workforce but also releases the capacity of highly skilled workers to handle more complex tasks (He et al., 2019). Another example of more efficient resource allocation is Babylon, an AI-based chatbot app contracted by the National Health Service (NHS) in the UK. It is a triage tool used to differentiate patients who only need assurance from those who need a face-to-face physician consultation (O'Hear, 2017). Beyond resource allocation, there are various tools that support hospitals in operational challenges to optimize patient flow. Predictive AI techniques help to identify critical junctures, track waiting times and prioritize patients. Healthcare providers can use this insight to efficiently move patients through the system and improve patient experience (e.g. Qventus).

AI for Insurances. The utilization of AI tools to increase efficiency is not only leveraged by providers but also by other supportive actors in the healthcare system. Health insurance firms, for example, automate claim submissions and adjudication, and use AI to detect fraud, waste and error (Allen, 2018; Saggi & Jain, 2018). An automated process for claim submission can reduce the burden on patients and the associated cost savings may allow insurance companies to scale up and provide more coverage (Thesmar et al., 2019). Efficient handling of fraud and abuse detection is crucial for insurance companies as they struggle to decrease healthcare costs. In 2018, the National Health Care Anti-Fraud Association estimated the fraud-related financial loss in the US between 3% and 10% of total health care expenditures (National Health Care Anti-Fraud Association, 2018). To counteract fraudulent claims, insurance companies implement machine-learning applications that review insurance claims to detect fraudulent and abusive cases (e.g. billings for unnecessary medical services or services that were not provided) (Kose et al., 2015). Additionally, AI can be used in claim adjudication to identify suspicious claims that need further verification or to detect abnormal price patterns among healthcare providers. This helps insurance companies to save time and monitor their costs (Thesmar et al., 2019). Some insurances have developed algorithms to identify health issues in the claims to help patients to get appropriate care services (Allen, 2018).

AI for Research in Life Sciences. Compared to the areas discussed above, the progress of AI application in life science research is far more advanced. High-throughput techniques like machine learning and deep learning techniques have been developed to confront challenges in the analytics of genomic and other '-omic' biological datasets (e.g. microbiomic, proteomic, metabolomic). Algorithms have advanced genomic analysis from a single-omic to a multi-omic approach, by considering a wide spectrum of '-omic' data (Bersanelli et al., 2016; McCloskey et al., 2013). Genomics research has contributed successfully to the treatment of complex diseases such as Crohn's disease or age-related muscular degeneration (Koboldt et al., 2013) and raises hopes to personalize medicine (e.g. individual risk assessment, medication) (Alyass et al., 2015; Gollust et al., 2012).

Pharmaceutical companies invest heavily in AI since it shows promising results in the realm of drug discovery (Wallis, 2019). Here, the most obvious advantage of algorithms is their capability to increase efficiency by examining millions of molecular structures, searching biomedical literature at high speed, as well as designing and making new molecules (Schneider, 2018; Smalley, 2017). An even more promising aspect is that algorithms can identify entirely new drugs operating detached from existing expert techniques (Freedman, 2019) and discover previously unidentified drug interactions leveraging pooled datasets (Hie et al., 2018). By predicting off-target effects, toxicity and the right dose for experimental drugs, unintended adverse effects can be reduced (Chakradhar, 2017).

AI for Patients. Another benefit of AI technology is that healthcare can be personalized to individual needs along all stages of care, including prevention, diagnosis, treatment and follow up

(Aroh & Cata, 2017). With their value-based care framework, Agarwal et al. (2020) recently highlighted that the availability of data and analytics tools creates an opportunity for healthcare to achieve more patient empowerment. Information about individuals' preferences not helps the achievement of a better understanding of what outcomes matter to patients but also improves their health decision-making (Hopkin et al., 2019). Treatment plans can be tailored to individual needs according to their genomic characteristics, personality traits or the situational context. Precision medicine aims to more systematically identify the right treatment based on individual characteristics (e.g. genetic profile) and to avoid adverse events for patients (Agarwal et al., 2020). To prevent the development of diseases or disabilities at early stages, analytical tools can also be used to predict patients' future probability of developing certain diseases given their current clinical data (Miotto et al. 2016).

AI for Public Health. AI can also help to manage population health by forecasting and tracking disease outbreaks or pandemics (e.g. COVID-19; (McCall, 2020)) and to improve health surveillance and speed of the response (Lalmuanawma et al., 2020). For example, AI can utilize location data from mobile phones for illness detection in real-world settings to predict areas of risk for future outbreaks (Sadilek et al., 2018). In another example, to improve the early detection of infectious diseases, methods of pathogen genomics are used to study genetic variants in infectious diseases, predict antibiotic resistance and assess vaccine safety and effectiveness (Khoury et al., 2016).

Public health can also leverage AI to develop targeted prevention strategies. Analyzing Electronic Health Record data and family history is an inexpensive tool for identifying individuals that require earlier and more intensive screening (Khoury et al., 2016). Furthermore, AI can increase the efficiency of public health services by the automated synthesis and interpretation of evidence. In the Human Behavior-Change Project, for example, Michie et al (2017) used AI and machine learning to make better use of the vast amount of accumulating evidence from various behavior change intervention reports to generate a knowledge systems with new insights about behavior change and improve prediction of intervention effectiveness (Michie et al., 2017).

2.3. Key Contributors to AI-based Health Solutions

To better understand how AI manages to improve health care delivery, one has to take a closer look at the individual components of the value creation process: input factors, transformation process and people.

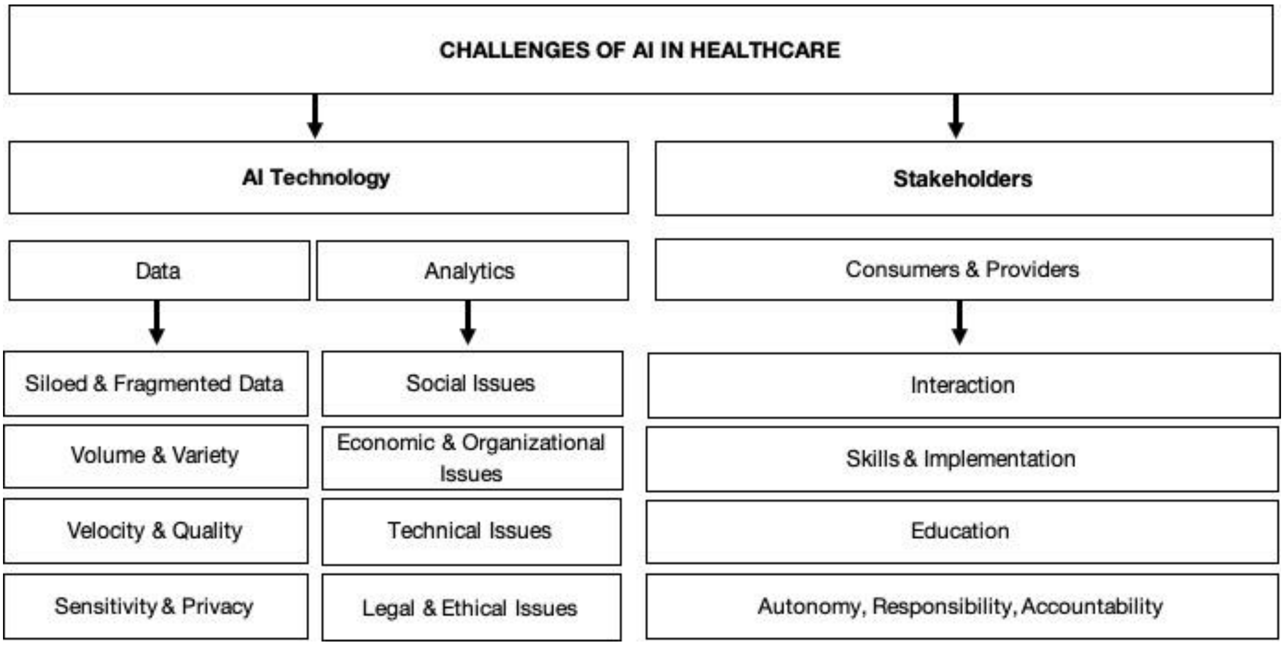
The most essential input factor for AI health applications is data. Healthcare is an information-rich environment where the amount of stored and collected data is vast and expanding rapidly. Among many others, they cover patient data, medical recordings (e.g. EHR, biomedical data), and insurance claims to sensor data and social media (Ward et al., 2014). Due to this variety and the high volume of healthcare data, this abundance of data is often referred to under the term big data. The ability to take advantage of all available information has become a critical ability to achieve healthcare goals. These data lay the foundation for improved decision-making (Janssen et al., 2017).

In isolation, that is, without considering the connections and context between data, these data are only partly informative. To obtain their full potential, the data need some form of transformation; this transformation, from data to value, is achieved by applying big data analytics (Holsapple et al., 2014). Big data analytics is an approach to combine, organize, process and analyze heterogenous big data (Saggi & Jain, 2018). Big data analytics applies advanced methods and technologies that are designed to extract significant value from analytical insights for many scenarios (Saggi & Jain, 2018). AI technologies such as machine learning algorithms are frequently applied in big data analytics. Health-related studies argue that big data and its integration with AI can greatly support diagnosis and predictive capabilities (Beregi et al., 2018; Schulz & Nakamoto, 2013).

AI value creation entails collecting data from various sources across the healthcare system, processing data by algorithms, and ends when data-driven decisions are made (Newell & Marabelli, 2015). Janssen et al. (2017) described this value creation as a flow or chain of activities and labeled it as a "big data chain". All these activities require bringing together multiple actors from different disciplines and diverse practices (e.g. developers, clinicians, researchers) to examine the under-explored relationships between the types of data (Janssen & Kuk, 2015), as each activity may be carried out by a different actor with a different skill set (Jansen et al. 2016). Even though there are many stakeholders of the healthcare system beyond consumers and providers of health services (e.g. payors, regulators) that are directly or indirectly involved in AI value creation, the consideration of each of their contributions to AI applications would be beyond the scope of this thesis. Therefore, this thesis focuses on providers and consumers as the relevant stakeholders that use AI applications for health care. AI applications in health services change the existing roles of provider and consumer (Larivière et al., 2017). Enabled by technology, patients are getting more actively involved and becoming innovators as they take part in the development and delivery of new services (Larivière et al., 2017). Individuals' input – not only in the form of data but also in defining their needs and preferences - is vital to decisions about treatment and wellness plans (Légaré & Witteman, 2013). Revealing their satisfaction and dissatisfaction with health processes and outcomes provides meaningful insights into patients' experience and helps to determine relevant dimensions of quality assessment (Donabedian, 1983). Providers and patients become collaborators in designing care and making decisions (Mesko et al., 2018). Providers thus act as enablers of the implementation of AI in health delivery, as they help and advise patients on how to adequately integrate AI into their health management and decision-making (Larivière et al., 2017; Mesko et al., 2017).

Input, transformation and people are all critical factors that determine the quality of AI solutions. The quality of decision-making based on AI solutions depends on the quality of the inputs (big data), the quality of the process (AI) that transforms inputs into output, and the capacity and capabilities of the persons involved in collecting, processing, and interpreting big data (Janssen et al., 2017). These are essential to enable the implementation of AI solutions that are safe, reliable and effective. However, each component holds challenges that create barriers to adoption. Figure 3 provides an overview of the challenges associated with the three main components of the AI value creation process: data, analytics and stakeholder. The following three sections of this chapter introduce each of the three components in more detail and discuss the related challenges.

Figure 3 *Overview of Challenges for AI Applications in Healthcare*



Notes: Own illustration; based on Rumsfeld et al. (2016)

2.3.1. Health Data: Foundation and Fuel for Advancement

Definition

The production of healthcare goods and services is a process that combines inputs to produce an output for consumption. Traditional input factors for production are labor, capital and raw materials. In light of technological progress, it becomes evident that information has become a new important input in healthcare (Murdoch & Detsky, 2013). Healthcare is a data-rich industry, which generates large amounts of data by keeping record of compliance and regulatory requirements, and various information about patient care (Raghupathi & Raghupathi, 2014). To generate value, most of the data stored in the health system still needs to be digitized. The digitization of these massive quantities of data (also known as big data) holds the promise to improve the quality of healthcare delivery by supporting a wide range of medical and healthcare functions (e.g. clinical decision support, disease surveillance, population health management) (Fernandes et al., 2012). Most definitions of big data follow the conceptualization of Gartner's IT Glossary that described big data as "high volume, high velocity, and/or high variety information assets that require new forms of processing to enable enhanced decision-making, insight discovery and process optimization.” The initial three V's (volume, velocity, and variety) have since been extended with: veracity, variability, visualization, and value (Gandomi & Haider, 2015; Newell & Marabelli, 2015). Table 3 summarizes these key dimensions of big data.

Table 3 *Seven Key Dimension of Healthcare Big Data: 7 Vs*

Dimension	Description	Example
Volume	Quantity, size of data	Scale of datasets in: • Terabytes • Petabytes • Zettabytes • Or more
Velocity	Speed of data generation and collection	Real-time patient data from regular monitoring such as: • Trauma monitoring • Electrocardiogram (ECG) • Daily diabetic glucose measurements
Variety	Heterogeneity of different data types and categories	• Structured and semi-structured: spreadsheets, electronic health records • Unstructured: text (e.g. handwritten physician’s notes), images (e.g. Magnetic Resonance Imaging (MRI), Computed Tomography (CT)), audio or video
Veracity	Quality of data or ‘data assurance’	Source of inconsistencies: • Inaccuracy (e.g. poor handwriting on prescription) • Missing data • Ambiguities • Deception, duplication (e.g. from different data sources)
Value	Capability to generate knowledge, insight for decision makers to take meaningful action	• Predicting and tracking flu outbreaks in real-time • Decreasing readmission rates

Dimension	Description	Example
Variability	Complexity and variation in data flow rates	Seasonal peaks in health effects and disease evolutions
Visualization	Presenting the data in a manner that is readable	Pictorial or graphical mapping of COVID-19 cases

Notes: Based on Saggi & Jain (2018)

Data Challenges

Despite the potential benefits that can be created for healthcare based on big data, there are still several obstacles and pitfalls that complicate this development. The main challenges are related to the following four characteristics of big data: data silos and fragmentation, volume and variety, velocity and quality, sensitivity and privacy.

Siloed and Fragmented Data. One of the main technical issues is siloed or fragmented data (Dimitrov, 2016). The data ownership is extremely fragmented across the healthcare system spanning hospitals, physicians, insurance companies, governments, technology companies, pharmaceutical companies and patients (Szlezak et al., 2014). Thus they are often siloed in different data repositories split across various systems and platforms with limited interoperability (Belle et al., 2015). Collecting and synthesizing data from multiple institution-centered silos is a challenging process (Dimitrov, 2016; Günther et al., 2017) which impedes the effective usage of data for further analysis (Szlezak et al., 2014).

Volume and Variety. A second challenge is based on the dimensions volume and variety. The volume of data is exponentially growing. Besides existing data from traditional sources (e.g. medical records, radiology images, research), new resources and devices (e.g. digital devices, sensors, social media, genomics) also generate huge amounts of data with ever-increasing speed. The accumulation of all these data is the underlying cause for the growing scale of big data (Raghupathi & Raghupathi, 2014). Retrieving, processing, and integrating these large-scale datasets poses a problem that requires novel approaches and analytical techniques (Sivarajah et al., 2017; Zhao et al., 2013). Even though data are now more available and accessible, only a small ratio can be properly captured and processed to generate useful information (Raghupathi & Raghupathi, 2014).

One reason that makes high volume data difficult for existing technologies to process is their inconsistent format. There is a lack of standardization in the healthcare system where diverse sources follow their own specific templates and formats (Sivarajah et al., 2017). This is in part attributable to health data variety. Health data are very heterogeneous in structure, format, type and source. The variety of data available can be classified according to two main sources: a) stakeholders and b) devices and digital resources. Both generate multiple data types including biological, medical, behavioral, environmental or administrative information (see Table 4). The potential of big data in healthcare lies in combining data from multiple sources on a population and individual level.

Table 4 *Types and Sources of Healthcare Data*

Data type	Description		Data inputs	Data source
Clinical	EHR	Patient related information	• Written notes & prescriptions • Medical history • Treatments • Medication	Hospitals/ Physicians
	Diagnostic	Diagnostic results	• Laboratory reports • Medical images/ Scans	Laboratories

Data type	Description		Data inputs	Data source
	Biomarkers	Molecular data	• Genotyping • Gene expression • Sequencing data • Omics	Laboratories
	Administrative	Demographic data & visit information	• Admission • Discharge • Transfer • Procedure codes • Patient feedback	Hospitals
Claims	Claims & billings	Medical reimbursement data	• Procedures • Hospital stays • Insurance details	Insurances
		Prescription reimbursement data	• Drugs • Dose • Duration	Insurances
Research	Clinical trails	Design parameters	• Compound • Sample & size	Pharma companies/ Research Institutes
Patient-generated	Behavioral	Wellness and lifestyle	• Daily steps • Sleep habits • Nutrition	Wearables Mobile sensors Smartphones
		Medical adherence	• Use of pillbox	Medical device/ Sensor
	Environmental	Social activity and network	• Likes • Tweets • Comments	Social Media Health community portals
		Neighborhood	• Mobile location	Smartphone

Notes: Adapted from Mehta & Pandit (2018), Agarwal et al. (2020)

While structured data can be easily stored, manipulated and analyzed by a machine (Raghupathi & Raghupathi, 2014), they only constitute 5% of all existing data (Cukier, 2010). Much of the highly valuable healthcare data exist only in an unstructured (e.g. written notes) or semi-structured form (e.g. emails) (Mehta & Pandit, 2018). Combining different formats, such as text data from patient records with physician's handwritten notes, heart rate measures from patients' mobile devices and ultrasound scans of the heart create structural and standardization issues (Kruse et al., 2016). Furthermore, there may be semantic interoperability issues due to different technical framings used across the healthcare system (Mehta & Pandit, 2018). As datasets become larger, more complex and more inexplicable, the limited mental capacities of human actors pose difficulties in deciphering and interpreting an unknown environment (Sammut & Sartawi, 2012). All these issues increase a complexity that humans are barely capable of processing without effective support. This highlights the need for big data analytics that have the potential to identify as yet unknown patterns by integrating various types of data (structured, semi-structured, unstructured), thus extending human analytical capacities (Gandomi & Haider, 2015; Mehta & Pandit, 2018). One such example is the development of better and more precise therapies for the right patient. Insights from medical real-time data, available through mobile apps or devices, can mean a difference between life and death. When infections or symptoms are detected early, a timely application of the right treatment may prevent patients from falling ill or reduce disease severity, morbidity, and mortality (Raghupathi & Raghupathi, 2014). Achieving these valuable insights for decision-making from big data is further determined by the third data challenge: velocity.

Velocity and Quality. Managing velocity - the high influx rate of rapidly generated real-time information - is a compelling prerequisite for rapid responses in critical settings (Chen et al., 2013). But the increased variety and high velocity impede the ability to prepare the data properly before analyzing them.

This automatically results in a fourth challenge: data quality or veracity. Even though big data holds the potential for the more precise targeting of treatment processes, higher diagnostic accuracy and better patient safety, veracity issues are an acute concern in healthcare. The quality of data inevitably influences the quality of decision-making (Janssen et al., 2017). Veracity issues are especially pressing in healthcare since patients' well-being depends on accurate information. Depending on the source, context and condition of the collection (Viceconti et al., 2015), data may be incomplete, ambiguous, messy or biased (Clark et al., 2016; Sivarajah et al., 2017). Decisions based on wrong insights due to e.g. missing data can affect the quality of care delivery (Hazen et al., 2014), and lead to false-positive associations (Rumsfeld et al., 2016).

Sensitivity and Privacy. Finally, healthcare data face the challenge of sensitivity and privacy issues. Medical data are highly sensitive. Individuals are particularly concerned about information regarding their sexual diseases, mental illnesses or infertility (Ermakova et al., 2015). Confidentiality between the healthcare provider and patient, and patients' legal ownership of their data, are mechanism that protect individual’s privacy. This conflicts with the aspiration for precision care (diagnosis, prognosis, treatment planning) that rests upon granular individual information. To tailor care to patients predispositions results must, in most cases, be relinked to patients' identities and thus cannot be fully anonymized (Viceconti et al., 2015). Consequently, misuse or data breaches like hacking represent major concerns (Agarwal et al., 2020). Even more concerning is the fact that even protected and anonymized information can be compromised if it is linked with other data sources (e.g. social networks, public sources) (Agarwal et al., 2020; Gostin et al., 2018). Especially individuals from vulnerable populations fear the consequences of stigmatization or discrimination (Agarwal et al., 2020).

A final remark about big data is its "low *value* density" (Gandomi & Haider, 2015, p. 139), meaning that the data received in their original form usually have a low value relative to their volume and needs further analysis. How valuable and reliable insights from big data are is highly correlated with the effective management of the other “V-dimensions” (e.g. cleaning dataset from inaccurate and ambiguous data) (Gandomi & Haider, 2015).

2.3.2. Technology and Analytics: Benefits and Risks of AI Tools

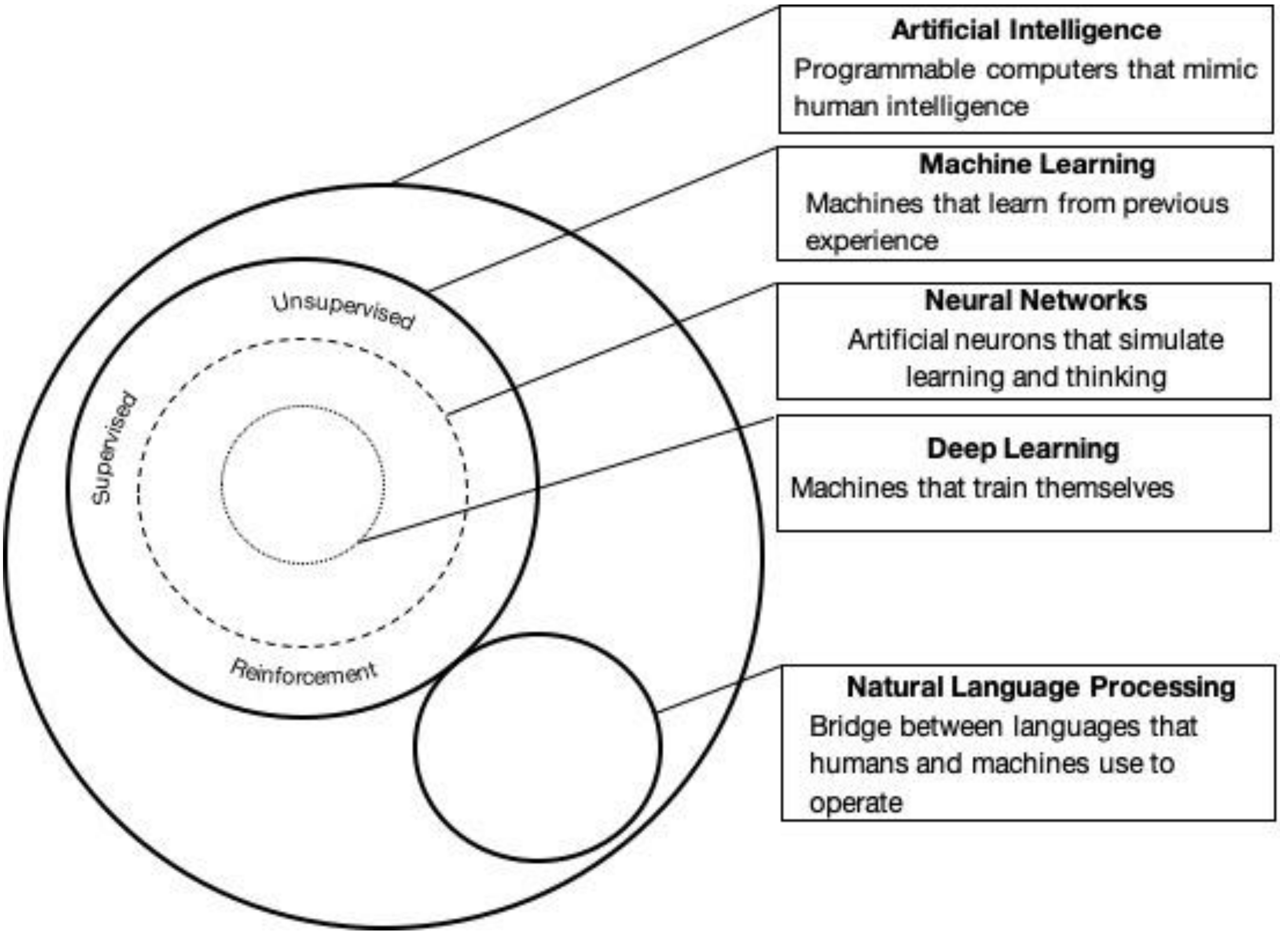
Big data are worthless in a vacuum. To unlock their potential for evidence-based decision-making, data need to be processed and analyzed (Gandomi & Haider, 2015). As discussed in the previous chapter section, big data entails several challenges that need to be properly addressed before it can improve the quality of care (Chen et al., 2012; Wang & Hajli, 2016). Big data analytics is comprised of several methodologies, procedures, and technologies that can transform raw data into valuable information (Patel & Patel, 2016). Advances in analytical techniques, especially machine learning, have been a major catalyst for dealing with these large and complex datasets. In contrast to traditional statistical methods, these advanced analytics can handle unstructured and high speed information (Murdoch & Detsky, 2013).

Various actors in the healthcare system benefit from big data analytics (e.g. providers, supporters, accepters). In clinical settings, it supports the early detection of disease, the accurate prediction of disease trajectory or the identification of deviations from healthy states (Mehta & Pandit, 2018). Additionally, patients also profit from targeted treatments, personalized risk predictions and cost-effective care (Bates et al., 2014). Rumsfeld et al. (2016) determined eight areas where big data analytics can improve healthcare quality: 1) predicting risk and resource use, 2) population management, 3) drug and medical device surveillance, 4) disease and treatment heterogeneity, 5) precision medicine and decision support, 6) quality of care and performance measurement, 7) public health and 8) research application.

Mining and extracting meaningful patterns from massive input data to reveal hidden patterns, unknown correlations, making predictions or other inferencing is at the core of big data analytics (Najafabadi et al., 2015; Patel & Patel, 2016). Gandomi & Haider (2015) distinguished two main processes in big data analytics: data management and analytics. Data management involves technologies to acquiring, storing and cleansing data, and preparing and aggregating them for analysis. Analytics refers to techniques that analyze and acquire intelligence from big data such as natural language processing, text mining, and machine learning (Janssen et al., 2017). One example is audio or speech analytics that analyzes and extracts information from unstructured audio data recorded through speech-driven clinical documentation systems. It supports the diagnosis and treatment of medical conditions such as depression or schizophrenia, where patients' communication patterns are affected (Hirschberg et al., 2010).

Given the breadth of big data analytics methods and techniques, this thesis focuses on the subset of algorithmic tools that are associated with the umbrella term of AI technologies. Techniques like predictive analytics or pattern recognition provide promising progress, especially in areas relevant to addressing healthcare problems. Figure 4 displays some of the subfields of AI that find application in healthcare and which are explained in more detail in the following paragraphs.

Figure 4 *AI and its Main Subsets*



Notes: Own illustration; modified from Ganasegeran & Abdulrahman (2020)

Machine learning. Machine learning is a subset of AI, in which machines learn how to complete a certain task without being explicitly programmed to do so. Machine learning uses raw unstructured data as input, transforms them so that they can be employed for learning, and chooses learning algorithms and tunes model parameters to generate the desired output (Zhou et al., 2017). Based on the nature of learning feedback, machine learning can be categorized into three main types: supervised learning, unsupervised learning and reinforcement learning (Russell & Norvig, 2016). In what follows, the three types are described briefly.

Supervised learning is suitable for predictive modeling via building relationships between inputs and the outcome of interest. In supervised learning data, need to be labeled for training, meaning data should be represented with attributes (e.g. body weight) and corresponding values (Cho et al., 2019). In this context, supervised means that, for its learning task, the system is provided with a specified task to map an input to an output based on a given example of input-output pairs (Zhou et al., 2017). According to this approach, a computer learns to recognize patterns among a set of data, so that when presented with new data, it specifies autonomously which pattern best fits the new information (Chakradhar, 2017). It has been applied to the prediction of disease risk (Chen et al., 2017), assessment of hospital performance (Downing et al., 2017) or determination of epidemics (Lalmuanawma et al., 2020).

The goal of unsupervised learning is to search and identify a previously undetected pattern in data with no pre-determined output or labeled data (Zhou et al., 2017). Thus, unsupervised learning analyzes data with only a minimum of human supervision (Alicante et al., 2016; Cho et al., 2019). Cluster algorithms (e.g. principal component, cluster analysis) group data through minimizing and maximizing similarities within and between the clusters (Jiang et al., 2017).

Reinforcement learning entails characteristics of both unsupervised and supervised learning. As in unsupervised learning, reinforcement learning operates without pre-labeled input-output pairs, but it is given feedback on its previous performance. Unlike supervised learning, there is no desired output that needs to be explicitly correct, hence feedback in the form of reward or punishment is associated with actions instead of output or correction of sub-optimal actions (Zhou et al., 2017).

The general focus of machine learning is the representation of the input data and the generalization of the learned patterns for use on future unseen data. The goodness of the data representation has a large impact on the performance of machine learning applications. A poor data representation is likely to reduce the performance of even an advanced, complex machine learning algorithm (Najafabadi et al., 2015).

Neural networks. Another method of AI are neural networks, a subfield of machine learning that draws inspiration from the biology of the brain. So-called 'artificial neurons' are designed to resemble the way neurons in the human brain are connected and simulate thinking (Chakradhar, 2017). Algorithms process incoming signals from the environment via interconnected nodes and capture complex non-linear relationships between input variables and output. Neurons are typically aggregated into layers. The basic architecture consists of an input layer and an output layer, and numerous hidden layers in between (Yu et al., 2018). Together multiple layers constitute an artificial neural network that mimics the distributed approach to problem-solving carried out by neurons in the human brain (Berner & La Lande, 2007). The hidden layers in a neutral network each perform different mathematical operations to transform inputs. Since modern neural networks are specified by millions of parameters like the number of layers, neurons per layer, number of training iterations, and learning rate, it is obvious that they require vast amounts of computational power to model complex relationships. But current graphical processing units (GPUs) can perform more than seven trillion floating-point operations per second (Yu et al., 2018). Thus, they are able to process hundreds of millions of medical images per day at a low cost, facilitating fast predictions of breast cancer from mammography images (input) and tumor indicators (output) (Dheeba et al., 2014).

Deep learning. Deep learning is a subset of machine learning and an extension to classical neural network techniques. It can be simply viewed as a neural network with a larger number of hidden layers so that it can explore more complex non-linear patterns in data (Zhou et al., 2017).

Compared to classical neutral networks, deep learning can analyze complex data with various structures and high dimensionality, such as image data (Jiang et al., 2017). As in machine learning deep neural networks can be either trained in a supervised mode - with training from known patterns and human-labeled input data - or unsupervised. A key differentiating feature of deep learning compared with other subtypes of AI is its autodidactic quality (Topol, 2019). While image and speech recognition primarily use supervised learning, deep learning takes advantage of unsupervised training in which training data can be generated automatically from unlabeled data without much human oversight (Raina et al., 2007). Deep learning algorithms use a huge amount of unsupervised data to automatically extract complex representations (Deo, 2015). It strives to emulate the hierarchical learning approach of the human brain. Deep learning solutions have yielded outstanding results in different machine learning applications including speech recognition, computer vision and natural language processing (Najafabadi et al., 2015).

Natural language processing. Natural language processing is a subfield of AI that refers to the capability of a machine to read, understand and derive meaning from human language. Human language is very subtle due to characteristics such as tone, irony or sentiment and mostly entails unstructured data. Reading human language entails a lot of difficulties for machines but to understand and convey the meaning of a sentences poses an even bigger challenge. Sentiment analysis, a technique of natural language processing in lexical semantics, derives meaning from individual words in context and was used to make inferences about peoples' mental states from social media communication (Calvo et al., 2017).

Speech recognition is one of the most common tasks of natural language processing that involves transforming speech, whether from audio or text, into a data structure that can be easily processed by machines. Basically, natural language processing methods are utilized for data management to extract information from clinical notes to supplement and enrich other types of structured medical data (Bedi et al., 2015; Miotto et al., 2016; Osborne et al., 2016), which can then be analyzed by other techniques (e.g. machine learning). This thorough, automated data acquisition helps to identify high risk factors, like postoperative complications from EHR data (Murff et al., 2011). It has also been applied in drug discovery for processing biomedical literature, mining the data of millions of molecular structures, designing new molecules, predicting off-target effects and toxicity, or determining the right dosage for experimental drugs (Chakradhar, 2017; Schneider, 2018; Smalley, 2017).

Technology Challenges

Despite the promises of AI technology in big data analytics, there are still several obstacles and pitfalls that impede implementation. The main challenges encompass the following areas that are subsequently discussed: social challenges, economic and organizational challenges, data challenges, technological challenges, ethical and legal challenges

Social Challenges. Social challenges arise when AI applications in healthcare contradict existing cultural norms of interaction, affecting both patients and care providers (Mesko et al., 2017). On the one hand, in the context of healthcare delivery, medical professionals need to acquire knowledge about how to interact with and work alongside AI tools. Applications of AI aim to provide clinicians with better and faster insights and to reduce the burden of highly repetitive work so that there is more time to focus on other aspects of patient care (Fogel & Kvedar, 2018). Medical education needs to impart technological and analytical knowledge and skills to better equip service providers with the necessary ability to effectively utilize AI for care delivery and patient communication (Wartman & Combs, 2018). On the other hand, patients' resistance to interacting with new technological tools and systems is one of the main barriers to AI adoption (Dwivedi et al., 2019). To mitigate patients' concerns and fears of technology, they need to be educated about data sharing and protection as well as the benefits and risk associated with AI (Xu et al., 2019). An additional challenge regarding AI adoption and implementation is the current connotation and perception of AI. For most people, AI is difficult to define and remains a mysterious concept (Dwivedi et al., 2019), resulting in unrealistic expectations and societal misunderstandings of AI capabilities, which in turn lead to lower acceptance (Sun & Medaglia, 2019). This is also enhanced by a lack of knowledge about the value and advantages of AI in the public health sector.

Economic and Organizational Challenges. Healthcare organizations raise concerns about economic and organizational challenges connected to the introduction of AI technologies. It requires substantial initial financial investment which might influence the profitability of service providers and may also increase treatment costs for patients (Sun & Medaglia, 2019). Another concern is the potential of misuse of AI technologies, which can be programmed to improve certain quality indicators or increase profits for certain drugs or tests without the awareness of the clinical user (Char et al., 2018). Most healthcare organizations still lack the internal and technological readiness that is needed to leverage AI. Resistance to redesigning existing processes, as well as a lack of knowledge about the best AI tools, are organizational challenges to the implementation of AI (Sun & Medaglia, 2019; Wang et al., 2018). Furthermore, to identify the right questions that can be answered with AI tools and to interpret analytical outcomes correctly, it is essential to have the right trained personnel. But the necessary skills that combine an understanding of the functional elements of healthcare processes, as well as technical skill to utilize AI, are scarce (Dwivedi et al., 2019).

Data Challenges. These challenges arise from the key characteristics of big data have already been discussed before (see chapter 2.3.1). Besides the challenges that relate to the basic characteristics of big data, more issues arise when data need to be merged and transformed for further analysis. Xu et al. (2019) highlighted how the validation of AI in cancer genomics heavily relies on getting patient outcome data that can be analyzed statistically. Patient outcome data, used for the training and evaluation of AI systems are scarce since the access to personal health information is restricted by legal protections (Lee & Gostin, 2009; Pesapane et al., 2018). The lack of standardization of data structures and format across different institutions in the healthcare system poses another barrier to AI implementation (Varga-Szemes et al., 2018). Moreover, there are no established processes such as clinical trials or peer reviews that assess the reliability of data used for AI application (Mesko et al., 2018). Algorithmic bias poses a serious threat to the validity of AI tools for healthcare as it may exacerbate pre-existing inequities in care (Gianfrancesco et al., 2018). Bias may already be embedded in many algorithms due to an underrepresentation of minorities and vulnerable populations in the datasets or missing data for these populations (Gianfrancesco et al., 2018; Topol, 2019). Racial and ethical minorities are generally underrepresented in clinical trials (Downing et al., 2016; Susukida et al., 2016), consequently analytical tools trained on these data could systematically produce more errors for those populations (Agarwal et al., 2020). One such example is the application of computer vision in dermatology for the detection of skin cancer. If an algorithm does not consider skin color for its diagnosis, because it is not adequately represented in the data, this will produce imprecise results for minority groups (Adamson & Smith, 2018; Esteva et al., 2017). Patients from vulnerable populations often receive care in a low-quality setting where patient-related health data may not be thoroughly documented in EHR, which fuels association bias in algorithms (Gianfrancesco et al., 2018).

Technological Challenges. One of the major technological challenges is surrounded by much controversy (Castelvecchi, 2016; Knight, 2017). Output by AI algorithms is often claimed to be a black-box (Newell & Marabelli, 2015), because users have no insights into the mechanism and determination of results (Sun & Medaglia, 2019; Topol, 2019). To discover patterns in the dataset and make predictions to support decision-making, algorithms process data and apply rules without human supervision. Associations and connections in the data are being made by the algorithm, with only a few individuals understanding what is included in the algorithm and why (Newell & Marabelli, 2015). This opaqueness has led to demands for explainability and transparency before an algorithm can be used for patient care (Kuang, 2017). Xu et al. (2019) highlighted the need for transparency and the reproducibility of experimental results. Mitchell (2019) further claimed that current AI systems do not have the essence of human intelligence and lack the ability to derive meaning. As algorithms neither understand the input that they process nor the output that they generate, they are particularly vulnerable to errors form hacker attacks. In this case, a hacker can make subtle alterations to input data that changes meaning but cannot be perceived by human users. This can lead to erroneous results, which can have detrimental consequences in the healthcare setting (Mitchell, 2019). Moreover, AI applications need validation and assessment of readiness before being implemented in patient care (Heaven, 2020). So far, many applications have only been developed in the laboratory and trained on small datasets, lacking real-world evidence (Rumsfeld et al., 2016). One recent example is IBM Watson Health's cancer AI algorithm, which was based on a small number of synthetic, non-real cases with very limited 'real' input data (Ross & Swetlitz, 2018). When put into practice, many treatment recommendations were shown to be erroneous. With a few exceptions (Hao, 2020), little direct real-world evidence so far demonstrates the actual effectiveness. Developers of AI tools also play a controversial role and are a potential source of bias. Algorithms are created by people who hold preconceived judgments, moralities, ethics and biases that they instinctively incorporated into their code. Even as we approach more sophisticated, unsupervised algorithms that build themselves, they still use inputs from human culture as a source of understanding which are loaded with stereotypes, discrimination and prejudices (Dwivedi et al., 2019).

Ethical and Legal Challenges. Decisions based on AI recommendations that might be erroneous or discriminative pose ethical and legal challenges. Discrimination as a result of biased AI systems violates ethical principles of equality and fairness (Dignum, 2017). Even though there have been first attempts at counteracting discrimination (e.g. fairness-aware data mining, integration of anti-discrimination criteria into classification algorithms) further detection and prevention mechanisms need to be established (Mittelstadt et al., 2016; Romei & Ruggieri, 2013). Against the background of ethical principles, the general question arises whether it is ethical and morally reasonable to deploy AI systems that make rules for human behavior. It is open to debate whether it is desirable to implement AI applications that decide detached from common human traits such as emotion or consciousness, especially in situations as in healthcare where humanness should play an important role (Wirtz et al., 2018). Even though there have been attempts to embed ethical principles into AI systems, Mittelstadt et al. (2016) claimed that "[…] ethical principles as used by human decision-makers may prove difficult to define and rendered [sic] computable" (Mittelstadt et al., 2016, p. 11). This becomes particularly relevant in situations where AI tools make moral decisions and need to choose between conflicting alternatives, such as an AI tool that decides on whether or not to resuscitate a patient with serious injuries (Bigman & Gray, 2018). This example highlights that AI applications without human oversight, particularly in healthcare where they might a face life-or-death decision, need to be capable of ethical reasoning before being applied fully autonomously in practice (Conitzer et al., 2017).

Furthermore, matters of responsibility and accountability are not sufficiently defined yet. Decisions and actions around AI tools are the results of the interaction of many different actors (e.g. developers, researchers, physicians, users). For instance, the question of who is responsible and liable arises when an AI tool makes decisions about a medical treatment that harms the patient's health. Is the developer, the supplier, the operator, the authorities or even the AI application itself responsible and liable for the consequences of the decision made? In situations where AI applications can cause harm, it is essential to specify the legal status of AI to remove uncertainties and determine legal responsibility and liability when AI applications cause harm (IEEE, 2017; Pagallo, 2018). For such cases where AI technologies replace (parts of) the decision-making process traditionally done by humans, there is as yet no adequate legal regulation that specifies how to incorporate non-human actors in the legal accountability system (Sun & Medaglia, 2019). How agency and responsibility are fairly shared remains unclear. Existing ethical frameworks only address individuals but not machines (Taddeo & Floridi, 2018). Another challenge arises from AI's ability to act autonomously and develop without human interference resulting in a so-called responsibility gap. This implies that AI systems act without human control, consequently, humans should not be held accountable for AI behavior that is out of their sphere of influence (Matthias, 2004). Even though there have been various approaches discussed to address the challenges of responsibility and accountability in the context of AI, so far there is no consensus (Johnson, 2015; Nagenborg et al., 2007; Santoro et al., 2008). New governance structures, regulations, ethical and legal frameworks need to be developed and enforced to prevent any harmful actions from AI (Taddeo & Floridi, 2018).

AI governance is a complex task and major challenge since it is associated with a variety of legal and regulatory issues including data, algorithms, infrastructures and humans (Gasser, 2017). Governments and other relevant stakeholders (e.g. industry representatives, NGOs) all have to agree on certain requirements in terms of explainability, transparency, fairness and accountability regarding AI to define regulations that comply with existing standards of democracy and human rights (Boyd & Wilson, 2017). There is a debate on where legal-regulatory frameworks are needed and whether exiting ethical and regulatory frameworks sufficiently cover the impact of AI (Cath, 2018). Veale et al. (2018) argued that many socio-technical challenges arising from AI are not adequately covered by existing data protection laws such as the European General Data Protection Regulation, due to the slow evolution of definitions and concerns. Even though there are various ethical principles and recommendations on how to address ethical issues of AI (IEEE, 2017), there is little evidence that those principles have yet translated into practice in the form of transparent ethical governance (Winfield & Jirotka, 2018). Since establishing a shared understanding of AI technologies and a normative consensus about what AI application is or is not desirable remains challenging, it is difficult to develop regulatory schemes. To deal with these challenges AI governance models need to be modular to provide interoperability of different frameworks and approaches (Gasser & Almeida, 2017). Since the field of AI applications is very broad it affects a wide range of legislative domains. The existing set of ethical principles in robotics and AI may be suitable and robust for many purposes, but the perception that these are universal governing regimes for all data-driven issues is misguided (Veale et al., 2018). Thus, for some types of AI applications and some regulatory domains, it might be useful to consider creating new, granular rules that are tailored to specific applications, while other types of AI can likely be regulated by small adaptations of existing laws (Palmerini et al., 2014).

2.3.3. Stakeholders and their Roles in the Context of AI

For a long time, the health system has followed a disease-oriented approach in which medically trained professionals held the decision-making power (Clark, 2014). With a limited set of tools, based on specific knowledge and professional experience, they made informed decisions about people's health (Mesko et al., 2017). The reorientation towards more patient-centered, value-based care delivery challenges existing interests and routines (World Health Organization, 2015). The rise of advanced technologies such as AI along with the accessibility of big data has increasingly disrupted existing structures in healthcare (Xu et al., 2019). In some areas, such as the accurate diagnosis of metastatic breast cancer, melanoma or eye diseases, some AI applications have already outperformed medical experts (De Fauw et al., 2018; Ehteshami Bejnordi et al., 2017; Haenssle et al., 2018). Besides the benefits of AI for healthcare, AI also initiates a paradigm shift that requires that existing roles and responsibilities of stakeholders need to be redefined (Mesko et al., 2018).

The digitization of healthcare provides access to information and insights to both healthcare providers and receivers, which transforms many aspects of the existing care delivery model.

Interaction. First, it changes the prevailing hierarchical patient-physician relationship. So far, patients have not been involved in the decision-making process about their health but have been mostly dependent on processes, information, knowledge and decisions of healthcare providers. The relationship has been characterized by power and information asymmetries where patients have insufficient skills to ascertain or understand the quality of the delivered service (Akerlof, 1970). At the same time, healthcare professionals alone had to take the burden of full responsibility for medical decisions, including the consequences. Digital health technologies reduce information asymmetries by making health information more readily available and comprehensible. This empowers patients to take more control of their health (i.e. self-management of health). Patients increasingly draw on multiple, heterogeneous resources (e.g. patient communities, health platforms) to gather information, make informed decisions and determine the impacts of treatments on their lives (Broom, 2016; Jadad et al., 2003). Direct access to health technologies creates transparency and improves accountability and productivity (Xu et al., 2019). This transforms the existing hierarchical relationship into an equal-level partnership with shared responsibilities in medical decision-making. Even though information enables patients to actively participate in care delivery and shape it according to their individual preferences and healthcare needs, the physician remains the crucial connector for medical decision-making.

Skills and Implementation. Second, resulting from the changes in the patient relationship, medical professionals now need to focus on different skill sets today. While patients have more access to information and technologies, there is the risk that they become overwhelmed by the vast amount of information when looking for appropriate solutions. Medical professionals are considered to have the highest expertise and experience, which they should use to guide patients in interpreting and judging information from AI to support patients in their self-management of health. They need to learn how to work alongside these new technological applications. Therefore, they need to understand how data-enabled applications operate in healthcare delivery and how they can make use of it to improve the quality of care delivery (Xu et al., 2019). Studies have demonstrated that synergies of clinicians and AI working together provided better results than either alone (Lakhani & Sundaram, 2017; Wang et al., 2016). Yet, the increasing workload for healthcare professionals concerning data management, analysis and patient communication has become a pressing burden (Mesko & Gyorffy, 2019). The application of AI tools aims not only to advise healthcare professionals with better and faster insights, thus reducing work involving repetitive tasks, but also enables them to focus on other aspects of patient care (Fogel & Kvedar, 2018). This causes a shift towards skills like empathy, social care and a human touch that are hard to automate or simulate by technology, but are essential for improved health outcomes (Hojat et al., 2011).

Education. Third, as advanced technologies like AI find their way into healthcare delivery, both care providers and receivers need to be educated. Educating healthcare professionals only on the foundations of biomedical and clinical science is becoming insufficient. Healthcare providers need to be trained on information and technology tools in healthcare to understand their benefits and limitations (He et al., 2019; Wartman & Combs, 2018). Research shows that a lack of technical knowledge and skills is the main reason for resistance (Boonstra & Broekhuis, 2010). In their review, Konttila et al. (2019) identified three key areas of competences in digitization that professionals need to acquire, including knowledge of digital technology (Sands et al., 2013), digital skills to provide good patient care (Kijsanayotin et al., 2009), and the ability to make ethical decisions regarding the use of digital technology in patient care (van Houwelingen et al., 2016; Wilson et al., 2013). Healthcare professionals also reported they need the motivation and willingness to accumulate experience with digitalization (Koivunen et al., 2015). At the same time, to facilitate patients' empowerment and involvement in decision-making, they need to be educated in dealing with health technologies and their implications. This involves clarification about the benefits and risks associated with AI in healthcare, as well as information about data sharing and protection. Since healthcare data are highly sensitive, healthcare providers need to be transparent about their procedures in data collection and use. Furthermore, healthcare providers need to enquire patient preferences for privacy and obtain their consent (Xu et al., 2019). Health literacy, coupled with knowledge about patients' rights, helps people to navigate the technology-intensive healthcare system and enables shared decision-making.

Autonomy, Responsibility, and Accountability. Fourth, the emergence of AI applications in healthcare challenges existing definitions of autonomy, responsibility and accountability in care delivery. The automatization of repetitive tasks may be in some parts a relief for healthcare workers, but it also poses a threat to their autonomy and legitimacy (de Grood et al., 2016). Previous studies showed that many providers perceive advances in technologies as a threat to their professional power within the medical encounter, resulting in damaged physician-patient communication which negatively impacts the quality of care (Broom, 2016; Cline & Haynes, 2001; Dedding et al., 2011). Particularly, this was the case for systems that formulate rules, processes and recommendations that guide physicians' behavior. Thus, by intervening in a domain that was heretofore exclusively claimed by physicians, AI threatens professional autonomy and diminishes adoption (Walter & Lopez, 2008). AI technologies inevitably alter the accountability in the patient-physician relationship. If a patient suffers an adverse event due to a decision made by an AI-based technology, it remains unclear who takes responsibility for the event (He et al., 2019).

Finally, healthcare providers that collect and analyze health data need to facilitate data sharing and transparency of algorithms (He et al., 2019). To continuously validate and improve AI algorithms, data need to be shared across multiple institutes. Therefore, it is essential to receive informed consent to facilitate these processes (He et al., 2019). This implies that notions of patient confidentiality and privacy, which traditionally require the withholding of information, need to be newly defined (Char et al., 2018). However, being transparent about data collection practices is essential to establishing trust and enabling patients' information disclosure (Anderson & Agarwal, 2011; Rohm & Milne, 2004; Willison et al., 2009). It should be good practice to share code and inputs used to generate results, combined with supporting documentation (Heaven, 2020). Transparency of algorithms is relevant on several levels. It is not only essential for evaluating accuracy and increasing interpretability (Sussillo & Barak, 2013) but also to identify bias (Char et al., 2018). Performance of algorithms can vary significantly when components such as the sensitivity of scale, empirical setting of hyperparameters and optimization processes are affected (Henderson et al., 2018; Xu et al., 2019). Transparency makes results more reasonable and improves their reproducibility (Wiens et al., 2019).

2.4. Quality Considerations of AI Health Solutions

Definition

The most prevalent definition of quality in healthcare was framed in 1990 by the Institute of Medicine as " the degree to which health services for individuals and populations increase the likelihood of desired health outcomes and are consistent with current professional knowledge" (Institute of Medicine, 1990; 2001, p. 22). The Institute of Medicine's definition has anchored the understanding of quality and later definitions are based on its core principles (World Health Organization, 2018b). The definition touches on several key aspects of quality. First of all, it encompasses "health services" in general, not restricting healthcare to only medical or patient care, but rather including a broad set of services (including acute, chronic, preventive restorative and rehabilitative care) that are delivered in various settings by different stakeholders (World Health Organization, 2018b). In addition, the Institute of Medicine specified "desired health outcomes" as patients' satisfaction and well-being as well as broader concepts of health status or quality-of-life measures. Finally, the definition refers to the concept of "current professional knowledge", which strengthens the movement of evidence-based care and stresses the dynamic and evolving nature of quality. The Institute of Medicine proposed six general dimensions of quality by stating that care should be safe, effective, patient-centered, timely, efficient and equitable. Similarly, in 2006, the WHO defined care to be effective, efficient, accessible, acceptable, patient-centered, equitable and safe. In a later refinement of this definition, the European Commission (2010) and WHO (2018) distinguished three main dimensions of quality from other attributes of good healthcare. While effectiveness, safety and people-centeredness represent the core dimensions, timeliness, equity, integration and efficiency are attributes of health services that are essential to realizing the benefits of quality (World Health Organization, 2018c). Table 5 summarizes the definitions of health care quality dimensions and attributes.

Table 5 *Definitions of Health Care Quality Dimensions and Attributes*

Key Dimensions	
Effectiveness	Providing evidence-based health services to all who could benefit, based on needs
Safety	Minimizing risks and avoiding harm to service users
People-centeredness	Providing care that responds to individual preferences, wants, needs, and values
Attributes	
Timeliness	Reducing waiting times and sometimes harmful delays for both those who receive and those who give care
Equity	Providing care that does not vary in quality on account of age, sex, gender, race, ethnicity, geographical location, religion, socioeconomic status, linguistic or political affiliation
Integration	Providing care that is coordinated across levels and providers and makes available the full range of health services throughout the life course
Efficiency	Maximizing the benefit of available resources and avoiding waste

Notes: Definitions based on WHO (2006) p. 9-10, (2018c) p. 13 and Institute of Medicine (2001) p. 7

Effectiveness represents the bottom line of health care quality, meaning that it determines whether care leads to improved outcomes of health status or quality of life (Institute of Medicine, 2001). Evidence-based care includes systematic patient assessment, accurate diagnosis, provision of appropriate treatment and proper patient counseling (Kruk et al., 2018). Health services that are low in effectiveness, such as incorrect diagnoses, can have detrimental consequences and contribute to treatment delays (Kruk et al., 2018). According to the Institute of Medicine, effectiveness is also reflected in the appropriateness of performed procedures. Effective care should avoid overuse (Brownlee et al., 2017; Thiels et al., 2017) of unnecessary care and underuse (Glasziou et al., 2017) of effective care. According to Chassin and Galvin (1998, p. 1002) overuse occurs when "a health care service is provided under circumstances in which its potential for harm exceeds its potential benefit". Underuse "is the failure to provide a health care service when it would have produced a favorable outcome for a patient (Chassin & Galvin, 1998, p. 1002).

Improving safety involves designing and implementing processes to avoid and prevent adverse outcomes that are caused by the healthcare process itself (e.g. Institute for Healthcare Improvement). Safety problems can take many different forms, including adverse drug events, adverse events and injuries due to medical devices, injuries due to surgical and anesthesia errors, health-care-associated infections, unsafe injections, falls, burns or misdiagnosis (Kruk et al., 2018). Errors occur along the continuum of clinical care functions and in the general environment of care. Consequently, safety measures have to be integrated at all levels of the care system to improve safety for patients as well as for those providing the care (Institute of Medicine, 2001).

The Institute of Medicine contrasted patient-centeredness with disease-centered and clinician-centered care and highlights the relational characteristic between patient and care provider (Institute of Medicine, 2001). It introduced the two subcategories of patients' experience of care and effective provider-patient partnership. The former relates to patients' perceptions of specific aspects in the process such as communication, skills or understanding of explanations. The latter entails forms of patient involvement in care or decision-making. An effective partnership is associated with an environment which encourages shared decision-making and patient skills and knowledge that provides patients with confidence to manage their health (Institute of Medicine, 2001). Kruk et al. (2018) went one step further in their conceptualization of patient-centeredness. They claim that the focus on people is crucial, not only because they are the main beneficiaries of health services, but also because they have agency over their health and health decisions. People are accountable agents of their health who should hold health system actors to account. People's health needs, knowledge and preferences should shape health care systems' responses. This is in line with Porter's (2019) and Agarwal et al.'s (2020) demand for value-based care that focuses on peoples' preferences and needs.

Why Is Quality Important? Impact of Healthcare Quality

The improvement of health outcomes is the essential imperative of healthcare systems and is incorporated in many frameworks that were developed to enhance the understanding of quality in the healthcare system (Institute of Medicine, 2001; Kruk et al., 2018; World Health Organization, 2018b). Healthcare quality can be understood as the basic prerequisite which serves as a means to accomplish the overall goal of improved health outcomes (World Health Organization, 2006). Health outcomes are diverse, thus it is essential to recognize that the definition of quality changes, depending on the outcome level at which it is assessed (World Health Organization, 2018b). It can address different patients' healthcare needs, such as a) primary prevention (staying healthy and getting help to avoid illness and remain well), b) acute care (getting better and getting help to recover from illness or injury), c) living with illness or disabilities (getting help with managing ongoing health conditions) and d) coping with end of life (getting help to deal with a terminal illness) (Institute of Medicine, 2001). While reduced mortality or morbidity may serve as a good quality indicator for acute care, quality of life or absence of health-related suffering would be more appropriate in palliative care (Knaul et al., 2018). The quality of care that people receive not only results in better health outcomes but also strengthens people's confidence in the health system (Kruk et al., 2018). High confidence positively affects individuals' decisions of when and where to seek care, meaning that people have trust their health services and are willing to make use of them (Ozawa & Sripad, 2013). Research suggests that quality perceived by patients might affect healthcare utilization patterns, retention to care and people's decision to bypass facilities. In a survey by the Lancet Global Health Commission, half of the respondents stated that the reason why they did not seek care (despite needing medical attention) was a quality concern (e.g. poor provider knowledge, long waiting times or disrespect) (Kruk et al., 2018).

Evaluating and Measuring Healthcare Quality

The WHO (2006) has emphasized that it is crucial to focus on quality in healthcare since, even in well-developed and resourced health systems, there are substantial variations in standards of health services' standards which cause serious concerns. Despite technological and medical advancements in healthcare, some systems still struggle to provide consistently high-quality care. This highlights the need to make use of advancements and new know-how and translate them into high-quality care (World Health Organization, 2006). To implement quality in care on a long-term basis, thus achieving improved health outcomes, it is necessary to evaluate and measure care on the quality dimensions of effectiveness, safety and patient-centeredness. The growing ubiquity and quantity of healthcare data, paired with substantial progress in information technology and measurement methodology, support the growing need for quality validation. Without measurement, it is difficult to assure high-quality service provision. The assessment of quality is the foundation for many stakeholders in the healthcare system to develop and implement strategies for better health outcomes (World Health Organization, 2018b). Given the theoretical nature of quality, with its changing aspects depending on definition and context, it appears inherently difficult to measure quality directly. Therefore, it is useful to define *a priori* quality indicators that provide quantitative information about quality dimensions (World Health Organization, 2018b).

The most frequently used framework for assessing and evaluating quality of care is Donabedian's paradigm of structure, process and outcome (Donabedian, 1983). It is a major way to classify quality indicators because it parallels clinical and organizational perspectives of care (Institute of Medicine, 2001).This proposed triad is grounded on the concept of 'input-process-output' used in industrial manufacturing and can be adopted as an approach to quality assessment independent of the underlying definition of quality. The measurement of the three components each provide a different piece of quality picture. Donabedian (1983) specified structure or input as the attributes of the setting in which care takes place. Attributes comprise material resources (facilities, capital, equipment, drugs, etc.), intellectual resources (medical knowledge, information systems) and human resources. Process, divided into technical and interpersonal processes, denotes activities regarding the use and transformation of resources in terms of what is done in giving and receiving care. Technical processes involve the application of medical science and technology, while interpersonal processes represent the management of interactions that occur between a service provider and consumers (Dagger et al., 2016). Outcome is defined as the effects of care on individuals' health status. The basic principle of the triad suggests that there are causal linkages between the components, meaning that, the first two components both directly and indirectly impact health outcomes, which stresses the importance of quality measurement throughout the entire value creation. Thus, a good structure affects the likelihood of good performance or process, which in turn can increase patients' health outcomes. Table 5 shows some examples of quality indicators for effectiveness, safety and patient-centeredness classified according to Donabedian's framework.

Table 6 *Examples of Quality Indicators for Donabedian's Triad*

	Donabedian's Triad		
	Structure	*Process*	*Outcome*
Quality Dimensions			
Effectiveness	• Availability of staff and equipment • Training expenditures for staff	• HPV vaccination for female adolescents • Transmit and track diagnostic orders	• Hospital readmission rate • Heart surgery mortality rate • Activities of daily living • Patient-reported outcome measures
Safety	• Availability of safe medicines • Volume of surgeries performed	• Safe surgery checklist use • Compliance to hygiene guidelines • False-positive rates of screening tests	• Incidence of hospital -acquired infections • Medical errors • Complications of diagnosis or treatment
People-centeredness	• Patients' rights • Availability of patient information • Patients' preferences	• Physician-patient communication • Patient-reported experience measures	• Activities of daily living • Patient satisfaction • Confidence in system • Patient-reported outcome measures

Notes: Adapted from WHO (2018b)

What mechanisms will (or should) be in place for quality control of AI in health services remains unclear. In the US, the Food and Drug Administration (FDA) noted that AI-based technologies are distinct from medical devices. It has defined a new category called Software as Medical Device (SaMD) and has expressed the need for an updated regulatory framework (Benjamens et al., 2020). In the European Union AI applications are regulated by the General Data Protection and Regulation and the Medical Device Regulation (Pesapane et al., 2018). According to the Medical Device Regulation, AI applications need to demonstrate their benefit and performance (e.g. diagnostic sensitivity and specificity). Beyond that, manufacturers need to ensure safety, repeatability, reliability, and provide a precisely intended purpose (Johner Institute). In addition, the General Data Protection and Regulation outlines a set of regulations that also affect AI implementation in the healthcare system in several ways. First, this concerns particularly Article 22 titled "Automated individual decision-making, including profiling" that describes the right of citizens to receive an explanation for algorithmic decisions (Art. 22, GDPR). This highlights the pressing importance of human interpretability in AI, but will presumably prohibit many AI applications currently in use (Goodman & S., 2017). Second, it raises the bar to obtain consent as it requires explicit and informed consent before any collection of personal data. Third, it shifts more power to the patients as it provides the tracking of data that are collected as well as the removal of data upon request (He et al., 2019).

This chapter provided a conceptual overview of AI in healthcare. After a definition and conceptualization of AI and its relevant subfields, the first section explains the general process of value creation in healthcare as well as the contribution of AI to this value creation. The second section discusses how different actors of the healthcare systems currently make use of AI applications. The third section discusses the contributions and challenges of data, technologies and stakeholder as key components for AI-health solutions. Finally, section four introduces the concept of quality in healthcare and the importance of its evaluation to achieve more patient-centered care.

The next chapter introduces the theoretical background of consumers role in AI health solutions and value creation on different levels. The first section presents Donabedian’s quality assessment triad as a framework for consumers contribution to AI value creation. Based on the theoretical background of Communication Privacy Management theory, section two then focusses on consumers’ contribution to AI input via their information disclosure. Several hypotheses are proposed that aim to answer research question one. Finally, section three elaborates on consumers’ response to AI output in form of the consideration of their compliance intentions with medical recommendations.

3. Theoretical Background

Consumers play a key role for the quality of AI's value creation process in healthcare. Out of the three key dimensions of healthcare quality introduced in the previous section, this thesis focusses on patient-centeredness as the factor most closely linked to consumers’ needs and preferences. Considering patients' values and preferences in the care process is essential to establish high-quality care. In its Global Strategy on People-centered and Integrated Health Services, the WHO (2015) called for a fundamental paradigm shift for care delivery. To provide better quality, people-centered health services should respond to their personal preferences and be coordinated around their health needs and expectations rather than diseases (World Health Organization, 2015). Patient-centeredness requires providers to adopt the perspectives of individuals and offer opportunities, skills and resources that they need to become actively engaged and make effective decisions.

There are three relevant concepts to achieve the goal of greater patient-centeredness: empowerment, engagement and co-production. Empowerment is about supporting individuals to take control of their health; engagement is about individuals being involved in designing, planning and delivering health services; and co-production refers to an active partnership, where service delivery is shared between patients and providers (Realpe & Wallace, 2010). The integration of these concepts in healthcare can have positive consequences on diverse patient-related outcomes (Castro et al., 2016). Several initiatives that have implemented patient-centered measures, for example, suggested positive effects on quality of care with higher patient safety (Longtin et al., 2010) and increased patient satisfaction (Fudge et al., 2008). Furthermore, empowerment provides patients with a sense of autonomy and capacity for managing new situations which has a positive impact on health-related quality of life (Kaal et al., 2017). Finally, patient-centeredness is also associated with other positive outcomes such as enhanced health status (Nafradi et al., 2018), adherence (Schoenthaler et al., 2017) and decreased healthcare utilization (Bertakis & Azari, 2011).

This highlights the need for a joint effort by the various actors, with all their dependencies and interdependencies, to improve quality in care. There are several reasons why the engagement of patients greatly impacts service delivery and health outcomes. The most obvious reason is better health. Ultimately it is the patients who are living with and responding to their health needs and know best about their capabilities and motivation that drive their decisions. For example, cancer treatment plans often vary in cost, life expectancy and the quality of life that they offer. Health service providers might not always be in the best position to make these trade-off decisions (Agarwal et al. 2020). To facilitate shared decision-making and improve the quality of consequent treatment recommendations it is important to measure and evaluate patients' preferences. However, tools that track needs and preferences are still barely implemented in clinical practice (Elwyn et al., 2012). Patients' input about their preferences helps to establish a better understanding of which outcomes are most relevant to them (Frank et al., 2014) and can be further incorporated into decision-making and care delivery (Légaré & Witteman, 2013). The engagement of patients in health decision-making provides them with more agency over their health and their health decisions. Empowerment reduces the imbalances between provider and patient within the traditional health system and establishes trust in providers and confidence in the health delivery (Kruk et al., 2018). This is essential for the willingness to use health care and to ensure an appropriate care uptake. To what extent patients' involvement is also important for AI value creation in healthcare is elaborated in more detail in the next section.

3.1. Consumers' Role in AI Health Solutions and Value Creation

The involvement of consumers is crucial for the achievement of patient-centered high-quality services of AI health applications. When using Donabedian's (1983) triad as a reference, this means that to improve quality, patients need to be involved throughout the whole value creation process. For AI applications, the first (input) and last (output) components particularly are the most relevant points of interaction with patients. In AI health solutions, process refers to the use and transformation of data into valuable insights that support decision-making. Here, quality is mainly determined by technical indicators such as assessment of performance compared to technical gold standards, security features or interoperability (Mathews et al., 2019). Given the required expertise and technical focus, patients' involvement in the process is only marginal.

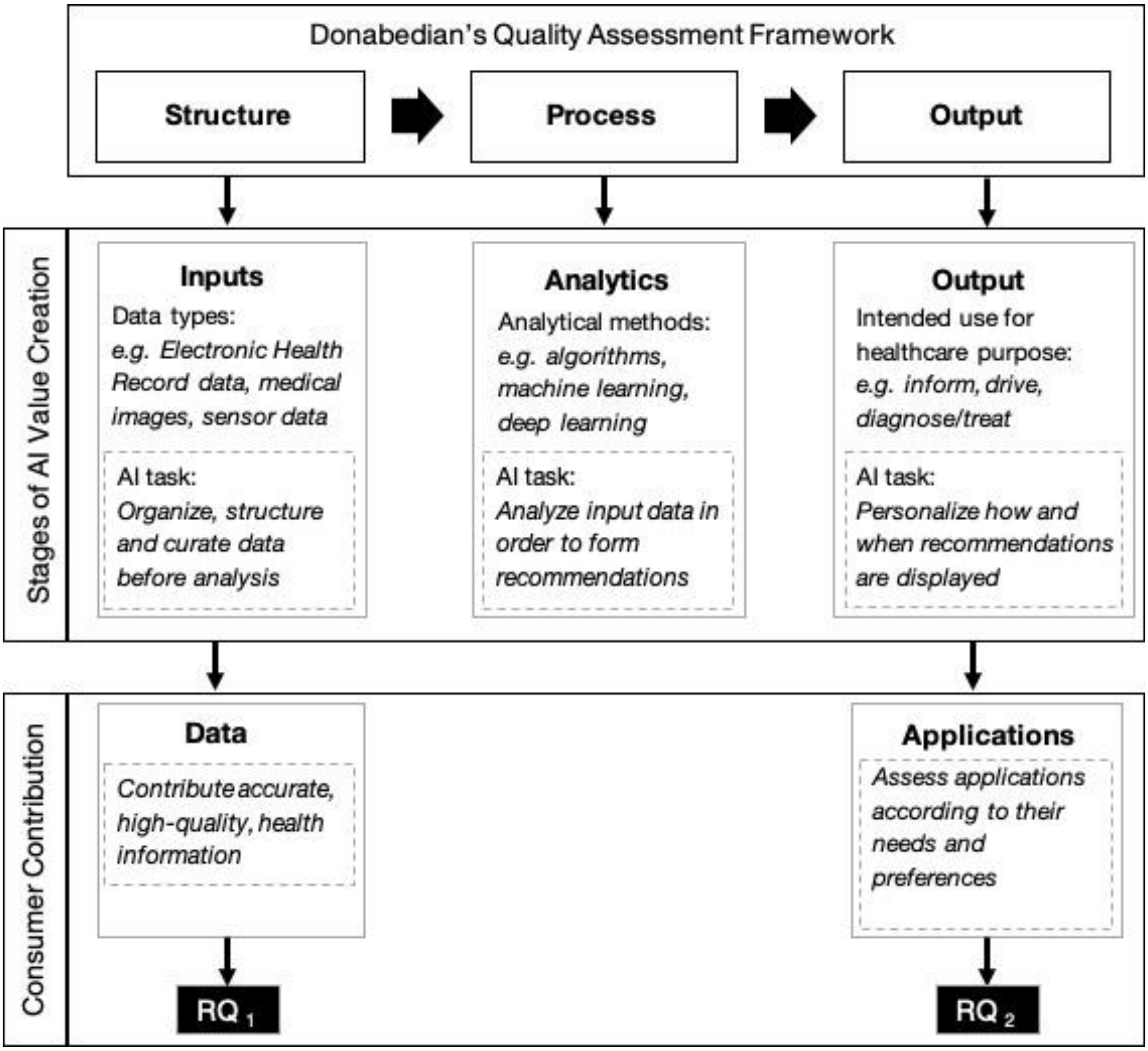
Hence, in part of this research, the focus lies on input and output of the value creation where patients' contributions are high. The input component is related to the first research question that explores factors influencing consumers’ health information management. The output component is linked to the second research question of this thesis, which investigates consumer responses to AI integration in healthcare services (see Figure 5).

Consumers’ first key role in AI value creation is related to the input for AI health applications: data. High-quality data are essential for all AI health applications. To ensure high quality it is necessary to involve patients, as the main contributor to health information, in all data-related issues. As per the adage 'garbage-in-garbage-out', the quality of the output inevitably depends on the underlying quality of the input factors (Najafabadi et al., 2015, p. 7). This highlights the need to shift the focus on patients who are the main contributors to health data. There are different stakeholders in the healthcare environment requesting patients' health information. Studies showed that individuals' intention to share health data varied with the requesting entity (Kim et al., 2015; Weitzman et al., 2010). While granular data collected on peoples' health can drive high-value care (e.g. precision medicine), they also pose a great risk to privacy (Agarwal et al., 2020). To establish an environment where patients feel comfortable in sharing health data, all stakeholders in the healthcare system have to acknowledge individuals' needs for confidentiality and security (Agarwal et al., 2020). The challenge is to deliver personalized health services while not deteriorating patients' trust (Martin et al., 2017; Martin & Murphy, 2017). In this context, it is important to understand patients' preferences for information sharing and to identify factors that facilitate and inhibit information disclosure.

The second key role of consumers in AI value creation is related to the *output*. The implementation of AI applications highly depends on patients' evaluations since they usually are the end-user of the services. In healthcare services, patients are often the final arbiter of what is acceptable and what is not across all the dimensions of quality (World Health Organization, 2006). Several indicators reflect patients' quality assessments, such as the measurement of patient experience, satisfaction, adherence, compliance and usage behavior. These indicators reveal patients' confidence in the system (Kruk et al., 2018). Positive patient experience is important for achieving high-quality care since it positively affects technical quality (Doyle et al., 2013), retention in care, adherence to recommendations and, eventually, confidence in the health system as a whole (Barbosa et al., 2012; Kruk et al., 2018). Prior research has already identified factors that contribute to patients' quality perceptions of a health service. They include, but are not limited to, technical quality and interpersonal factors such as empathy (Hojat et al., 2010; Ware et al., 1983), convenience and communication (Marshall & Hays, 1994). In line with these dimensions, Wirtz et al. (2018) suggested that consumer acceptance of AI in service delivery is determined by its capability to deliver functional, relational and socio-emotional needs. How these convert into patients' evaluations of AI health solutions yet remains unclear. Research question two of this thesis aims to address this gap and intents to gain more insight into this mechanism.

Figure 5 summarizes how Donabedian’s quality assessment framework applies to AI value creation. Furthermore, it displays consumers’ contributions to AI value creation and presents the connected research questions. The next section explains in more detail how consumers contribute to the quality of input aspects and develops several hypotheses that aim to answer research question one. The subsequent section then focuses on research question two and consumers’ contribution to the assessment of AI output.

Figure 5 *Consumers' Contribution to Quality in AI Value Creation for Healthcare*



Notes: Based on U.S. Food and Drug Administration (FDA) (2018)

3.2. AI Input: Consumers' Information Disclosure and Protection

AI applications in healthcare are expected to advance medical decision-making systems by leveraging the large amounts of patient-level data. Decision-makers such as healthcare organizations or clinicians can benefit from improved workflow and reduced medical errors. Healthcare analytics model the risks of adverse events based on clinical and/or non-clinical patterns in data.

The prediction of future health-related outcomes, such as medical complications (Stevens et al., 2001), treatment responses (Meyer et al., 2014), patient readmissions (Bardhan et al., 2015) and patient mortality (Tabak et al., 2014) increase efficiency and precision, to the mutual benefit of patients and healthcare organizations.

AI applications can also consider various patient-specific factors and thus can assist healthcare providers in assessing patients’ risks more granularly and attain the goals of preventive and personalized care (Li et al., 2017). Furthermore, pharmaceutical companies invest in AI since it shows promising results in the realm of drug discovery (Wallis, 2019). Here, the most obvious advantage of algorithms is their capability to increase efficiency by examining millions of molecular structures, searching biomedical literature with high speed as well as designing and making new molecules (Schneider, 2018; Smalley, 2017). Another benefit of AI is that healthcare can be personalized to individual needs along all stages of care, including prevention, diagnosis, treatment and follow up (Aroh & Cata, 2017). With their value-based care framework, Agarwal et al. (2020) highlighted that the availability of data and analytical tools creates an opportunity for healthcare to increase patient empowerment. Information about individuals’ preferences not only helps to better understand of what outcomes really matter to patients, but they also improve decision-making (Hopkin et al., 2019). More importantly, treatment plans can be tailored to individual needs according to their genomic characteristics, personality traits or situational context.

Sharing personal health information is essential to create AI-based healthcare services. To realize the benefits for preventive and personalized care, algorithms must be trained on large health information datasets that can be analyzed for wellness and disease trends. Incorporating this information will not only empower consumers but also enable health systems to improve patient care. However, quality is a critical prerequisite for data used in AI applications since erroneous or ambiguous data can have detrimental effects on peoples' health. To answer research question one of this thesis, it is critical to understand how individuals make decisions about their information sharing. Information boundary management, which will be explained next, provides the conceptual framework for studying individuals’ information sharing.

Information Boundary Management

The theoretical foundation for this context is the Communication Privacy Management theory (Petronio, 2002), which was developed to understand how individuals make decisions regarding information disclosure within interpersonal relationships. To illustrate how individuals control and govern their information flow with others, Communication Privacy Management theory uses the metaphor of boundaries. A boundary represents a psychological contract between the information sender and its receiver and defines the amount, nature and circumstances of the information exchange (Stanton, 2003). When individuals wish to reveal private information, the boundary is open; there is no need to regulate the way they control potential risk and information flow freely (Petronio, 1991). Boundaries are closed when individuals wish to restrict information exchange.

Communication Privacy Management theory posits that individuals frequently grant or deny access to private information by applying different types of rules to manage information exchange processes with others. These rules about boundary opening and boundary closure are dynamic psychological processes of regulation by which people attempt to control the flow of intimate information. Boundary rule formation is determined by criteria that are salient to the individuals at the point of time they make the decision such as culture, gender, context, motivation and risk-benefit ratio (Child et al., 2012). Thus, depending on the situational and personal factors, an attempt by an external entity to overcome these boundaries may lead to the disclosure or restriction of personal information.

Boundary rule formation can be context-specific in that it depends on the status of the relationship between the sender and the receiver as well as certain justice considerations, such as the mission-relatedness of the information (Stanton & Stam, 2003; White, 2004). For example, a person may develop different threat perceptions regarding the same personal information being accessed by different healthcare organizations or entities (Li & Slee, 2014). Individuals open their boundaries when they do not perceive an undesirable level of vulnerability to negative reactions by the information receiver, and when they expect a fundamental benefit from releasing the information (Stanton, 2003). These conditions are conceptually close to Boon and Holmes's (1991) definition of trust as "positive expectations about another's motives and with respect to oneself in situations entailing risk” (Boon & Holmes, 1991, p. 194). In the healthcare setting, information disclosure varies with the type of organization involved in the disclosure exchange, the level of trust and concerns related to the requesting entity (Anderson & Agarwal, 2011; Willison et al., 2009).

Furthermore, the risk-benefit criteria in patients' rule formation accounts for different types and levels of risk in their decision on information disclosure. In the healthcare context, one such risk factor is related to certain types of information that can be particularly sensitive (e.g. infertility, mental illness) (Bansal et al., 2010; Mothersbaugh et al., 2012). Moreover, the purpose for which the information is requested in the healthcare setting also makes different risks salient, thereby influencing the rules applied for information exchange (Anderson & Agarwal, 2011). People have different levels of trust in healthcare organizations that impact rule formation. Besides trust, individuals open boundaries if they have positive expectations about other's motives concerning themselves (Boon & Holmes, 1991; Stanton, 2003). If, in contrast, individuals suspect opportunistic motives behind the information request, the perceived risk from releasing information becomes more salient, leading to boundary closure. The next section discusses relevant contextual and risk factors of the healthcare context that influence individuals’ boundary rule formation.

Contextual and Risk Factors Influencing Information Disclosure

One of the most studied inhibitors to health information disclosure are privacy concerns (Anderson & Agarwal, 2011; Bansal et al., 2010; Kenny & Connolly, 2016). Privacy concerns not only diminish individuals’ disclosure intentions (Campos-Castillo & Anthony, 2015), thus limiting the amount of data that individuals are willing to share, but can also lead to more defensive behavior in the form of falsification of information (Son & Kim, 2008; Wirtz & Lwin, 2009). Even though privacy concerns are an inherent part of individuals' information management, the mechanism of other risk and contextual factors affecting information disclosure still needs to be better understood.

For example, information sharing is highly dependent on context and risk factors associated with the health organization requesting or receiving the information. Individuals' preferences for data sharing vary by the type of information collected, purpose and the recipient (Roeber et al., 2015). Different types of information imply different levels of sensitivity, which is another risk factor affecting information disclosure. Individuals are less willing to share sensitive (e.g. sexual health information) vs. less-sensitive (e.g. medication) information (Caine & Hanania, 2013). Information sensitivity increases privacy concerns, which in turn reduce individuals' willingness to share information (Anderson & Agarwal, 2011) or increase misrepresentation of true information (Lwin et al., 2007). This is especially the case for people with a poor health status (Bansal et al., 2010; Ermakova et al., 2015). Sharing sensitive data increases individuals' vulnerability to harm and the potentially adverse consequences, which results in higher levels of protective behavior in the form of data misrepresentation (Martin et al., 2017). Organizations' transparency policy about data collection practices, as well as granting consumers control over their data, was found to reduce the effect of privacy concerns on information disclosure (Martin et al., 2017), but only in cases of low information sensitivity (Lwin et al., 2007). In contrast, offering individuals some level of control over their data proved to be more effective for information with high sensitivity (Mothersbaugh et al., 2012).

The purpose for which data is shared is another contextual factor influencing information disclosure. In terms of data sharing for research purposes, Aitken et al. (2016) found that individuals were conditionally supportive when they perceived a potential benefit and trusted the organization collecting the data. Having autonomy and control over their data was another criterion facilitating open data sharing, while concern over confidentiality and data abuse restricted data sharing. Under the premise of control (e.g. consent, permission), individuals are more likely to share their data for research rather than for healthcare purposes (Kim et al., 2015). Among the main drivers for donating genomic data research are altruistic factors (e.g. contributing to scientific research in general, supporting research for certain diseases) as well as personal benefits (e.g. identifying personal predispositions for certain diseases, therapeutic relevance). Concern about discrimination or misuse of data or government abuse are among the major discouraging factors of information disclosure (Hill et al., 2013; Thiebes et al., 2017). Other barriers include a lack of awareness of the value contribution of data and the concern about data being used for profit generation (Aitken et al., 2016; Pickard & Swan, 2014).

These concerns may in part be also related to the recipient of the data. Individuals' data-sharing preferences vary with the requesting entity. While they are willing to share personal health information with physicians, hospitals or research institutes, they are less willing to do so with governments, for-profit organizations or for insurance firms (Grande et al., 2013; Pickard & Swan, 2014). Individuals have different levels of trust in healthcare organizations, which influence their willingness to share information (Anderson & Agarwal, 2010). The positive effect of trust on information sensitivity and privacy concerns is one of the reasons why it is a major facilitator for information disclosure (Rohm & Milne, 2004; Weitzman et al., 2010). Besides trust, fairness perceptions about organizations' data collection and usage procedures reduce privacy concerns (Son & Kim, 2008; Wirtz & Lwin, 2009).

Another factor that is of particular interest to the present research is the perception of motives (Child et al., 2012). This becomes relevant when individuals wonder why a healthcare organization might ask for their personal information. In the following sections this thesis argues that, first, differences in the type of requester (for-profit vs. not-for-profit organization) will influence individuals’ perception of motives related to the data request from the organization and second, that consumers use different tactics of information control, in the form of information self-disclosure and falsification intentions, in response to these perceived motives.

The Type of Requester of Personal Information and Motive Perception

Based on differences in objectives, performance criteria, ownership levels and trust (Grande et al., 2013; Hill et al., 2013; Kim et al., 2015; Rohm & Milne, 2004; Weitzman et al., 2010; Willison et al., 2009), individuals may attribute different motives to health organizations when these organizations request personal information. This is because individuals make use of cues available in their environment to make causal inferences. While the ownership structure of pharmaceutical companies often reflects the status of for-profit organizations whose activities are governed by capital market-oriented structures, the ownership structure of hospitals often reflects the status of not-for-profit or public organizations, mostly financed by the state, charities or research and education funds.

Attribution theory illustrates the underlying cognitive process by which individuals assess the motives behind others' behaviors. It is based on the assumption that individuals seek to develop an understanding of the events that they observe or experience (Heider, 1958; Kelley, 1973). Individuals, exposed to some form of marketing activity by organizations (here: requests for personal healthcare information), make inferences about their motives, which then drives evaluations and behaviors (Campbell & Kirmani, 2000; Ellen et al., 2000; Forehand & Grier, 2003; Groza et al., 2011). Individuals have been shown to attribute two main types of motives: altruistic motives that aim at the well-being of individuals external to the firm and egoistic motives that focus on the potential benefit to the organization itself. Prior research used various labels for these two motives, including socially motivated versus profit-motivated (Becker-Olsen et al., 2006) and public-serving versus firm-serving (Forehand & Grier, 2003).

Altruistic motives are attributed to organizations when individuals perceive that they perform a behavior because they care about others' welfare (Rifon et al., 2004) and are driven by sincere and benevolent intentions (Vlachos et al., 2009). These attributions affect individuals' responses positively (Dean, 2002). Given their not-for-profit ownership (and the mission behind this structure to benefit the community), individuals are expected to attribute higher altruistic motives to university hospitals' requests for personal information (as an example of a healthcare, research-relevant, not-for-profit healthcare organization) compared to when pharmaceutical companies request personal information (as an example of a research-relevant, for-profit healthcare organization) for healthcare research purposes.

Egoistic motives center around the ego-driven needs and self-interests of organizations. Goals such as increased market share or publicity are highlighted. Egoistic motives cause negative responses among individuals towards organizations (Becker-Olsen et al., 2006) because their activities are judged as manipulative (Vlachos et al., 2009). Given their for-profit ownership (and the mission behind this structure to benefit the organization), individuals are expected to attribute egoistic motives to pharmaceutical companies, as compared to university hospitals, when they request personal information for healthcare research purposes. The former are inferred to exist due to their ability to profit from their relations with consumers (Rifon et al., 2004), while this might not be true for the latter. In this context, consumers evaluate for-profit organizations from a profit maximization logic, where they expect the organization to act mainly out of self-interest or egoistic interests (Alcañiz et al., 2010; Dean, 2002), while this might not be the case for not-for-profit organizations such as a university hospital. Based on the arguments explained above, the initial hypotheses are stated as follows:

> **Hypothesis 1a** *Attributions of altruistic motives for the request of personal information for healthcare research purposes will be lower for pharmaceutical companies compared to university hospitals.*
>
> **Hypothesis 1b** *Attributions of egoistic motives for the request of personal information for healthcare research purposes will be higher for pharmaceutical companies compared to university hospitals.*

Tactics of Information Control

The motive perceptions introduced in the previous section can elicit different responses from consumers. Patients may for example restrict access to their health information if they perceive more risks than benefits. In their conceptual framework on identity management, Zwick and Dholakia (2004) proposed that individuals apply certain tactics to maintain control over the externalization of their personal information towards others. They manage the digital representation of their identity by the amount and accuracy of personal information that they share with third parties. In response to companies' data collection strategies, consumers use different tactics of information management (see Table 7) that enable them to control the information flow and limit accessibility.

Table 7 *Four Tactics of Individuals' Information Management*

	Level of Accuracy	
	High	*Low*
Amount of Information		
High	IDENTIFIABILITY Disclosing all information with high accuracy	ANONYMITY Disclosing many and potentially inaccurate information
Low	CONFIDENTIALITY Disclosing limited but highly accurate information	SECRECY Disclosing little and potentially inaccurate information

Notes: Adapted from Zwick & Dholakia (2004); Dinev et al. (2013)

Dependent on the amount and accuracy of the information, the theoretical framework classifies four tactics of information management: identifiability, anonymity, confidentiality and secrecy. Identifiability reflects consumers' unrestricted sharing of highly accurate data, while secrecy is the contrary. A third tactic, confidentiality, differs from identifiability in that individuals limit the amount of information they share but maintain the same level of accuracy. Anonymity, finally, is a tactic that allows the consumer to disclose large amounts of inaccurate personal information (Zwick & Dholakia, 2004). This thesis considers two main consumer responses that result from these tactics: self-disclosure and falsification.

Self-disclosure. With the rise of AI applications in the healthcare setting, information exchanges between consumers and healthcare organizations gain in importance. Responses to these requests have significant implications for healthcare organizations that are increasingly dependent on data-driven decision-making. Since health data are perceived as sensitive, individuals ascribe a high risk to revealing such information and are often reluctant to disclose sensitive information (Bansal et al., 2010; Dinev et al., 2013; Kehr et al., 2015; Phelps et al., 2000).

Further concerns are the exposure of personal health information and the legitimate use of health data. One of the main reasons is the fear of real consequences of discrimination in health insurance and employment-based discrimination, depending on preexisting health conditions (Bardhan et al., 2020). The growing reluctance of patients to give their data to healthcare organizations is not only related to privacy risks but also to the perception of being exploited. Even if patients release personal information for purposes of AI-based research on improving health, healthcare organizations earn the majority of financial benefits, while the contributors may get nothing (or only a little) in return (Cassel & Bindman, 2019). Since healthcare research is increasingly performed by for-profit companies that have to serve investors' needs (according to the rules of the capital market), individuals will be even more cautious with their data. Even though these organizations may protect individuals' privacy by only using anonymized data, identities can still be leaked by third-party firms that link pieces of data together (Gostin et al., 2018).

Falsification Intentions. Besides their hesitancy in self-disclosing personal health information, individuals engage in control strategies to protect their personal data. In particular, they falsify information – that is, they create and convey wrong information to others (Argo et al., 2006) to protect their privacy (Jiang et al., 2013; Lwin et al., 2007). Misrepresentation facilitates self-protection in response to a request for sensitive information. To reduce their vulnerability to opportunistic behavior, individuals might fabricate such information. This enables them to keep their privacy and simultaneously placate or satisfy others (Jiang et al., 2013). Misrepresentation of information does not disturb the social exchange but allows individuals to proceed with an interaction. This behavior is detrimental to the effectiveness of big data technologies in healthcare since it may negatively affect the validity and reliability of results and trigger major downstream consequences. In the healthcare environment, accurate information is critical for achieving high-quality outcomes for patients. To this end, this thesis considers both factors of disclosure management: the likelihood to self-disclose personal information and the likelihood to falsify this information.

According to Communication Privacy Management theory individuals control their information flow with others by applying certain rules that manage the information exchange process. At the point of the information request, individuals decide on whether to open or close their information boundaries based on contextual or risk criteria salient in the specific situation. Thus, the underlying motives that individuals attribute to a health organizations' information requests might influence individuals' information disclosure tactics. This thesis argues that, first, the perception of altruistic motives will result in the opening of borders and facilitate information flow between the individual and the healthcare organization (and hence affect self-disclosure of information), and, second, the perception of egoistic motives will prompt individuals to make information-protective behavior more likely (in the form of falsification of information). The following section explains the arguments in more detail.

The Downstream Consequences of Perceived Motives

Individuals are aware that they need to release personal information in exchange for certain benefits to satisfy their needs (Norberg & Horne, 2013). The exchange of information is part of what is known as a social contract: individuals have something of value to others and both parties decide to engage in a mutually agreeable trade (Martin & Murphy, 2017). Perceptions of altruistic-driven motives indicate that healthcare organizations emphasize the creation of social and common benefits. As a consequence, these perceptions might open the boundary and make individuals more likely to disclose personal information. Altruistic motives lower the barrier for action. Hence, altruistic motives should act as a mediator between the type of organization that requests personal information (pharmaceutical company vs. university hospital) and the willingness to self-disclose personal information.

Hypothesis 2a *Attributed altruistic motives mediate the relationship between the healthcare organization that is requesting personal information (pharmaceutical companies vs. university hospitals) and an individual's self-disclosure intentions.*

The social contract between requesters and releasers of personal information comprises commonly understood obligations or social norms for both parties; this is critical for the prevention of opportunistic behaviors (Li, 2012). Most importantly, the present study assumes that when individuals attribute egoistic motives to the information requester, they might be concerned that the organization may not honor the social contract, so that they act only in their own best interest. The egoistic motive might fuel consumers' skepticism and lead to negative reactions (Forehand & Grier, 2003). To retain control while still reaping the benefits of the exchange, individuals may misrepresent their data (Lwin et al., 2007; Lwin & Williams, 2003). This need for a defensive tactic might stem from the underlying motives that individuals attribute to the information request. Subsequently, individuals will be more likely to misrepresent their data in the information exchange with the health organization. Therefore, this thesis postulates that egoistic motives should act as a mediator between the type of organization that requests personal information (pharmaceutical company vs. university hospital) and the willingness to falsify personal information.

Hypothesis 2b *Attributed egoistic motives mediate the relationship between the healthcare organization that is requesting personal information (pharmaceutical companies vs. university hospitals) and individuals' falsification intentions*

To better understand in which circumstances individuals' motive perceptions might facilitate or harm information sharing with different healthcare organizations, the next sections introduce two potential moderators: message appeal and message endorser. The two sections discuss how the message appeal and message endorser as persuasion strategies in organizations' communication can be used to shape individuals' perceptions about corporate motives, and thus influence their information management.

Message Appeal: Self-benefit vs. Others' Benefit

Individuals' motive attributions can be influenced by communication (Rifon et al., 2004) because message recipients' causal inferences are strongly linked to salient information or features that are present in the environment (Heider, 1958). Since healthcare organizations attempt to create positive perceptions about their underlying motives, they use various communication tactics (Vanhamme & Grobben, 2009). The right tactic is crucial to avoid skepticism and to ensure message persuasiveness (Groza et al., 2011). In particular, in research into consumers' prosocial behavior such as donations or ethical consumption, it was found that whether the message highlights the benefits for others or the benefits for the individual affects their behavior approach (White & Peloza, 2009). The following paragraphs provide arguments as to why such message appeals matter in the context of healthcare providers asking for personal information.

Others-benefit appeals highlight other individuals or the society at large as the main beneficiaries (Fisher et al., 2008), while self-benefit appeals highlight the giver as the main beneficiary of the exchange (White & Peloza, 2009). This thesis argues that individuals will respond differently depending on who communicates others' (vs. self-) benefits as regards the intentions to disclose personal information. Others-benefit appeals are especially effective in non-commercial exchanges (Rothschild, 1979) and in the context of social goods, because they trigger an empathy-helping response in individuals (Fisher et al., 2008). Not-for-profit healthcare organizations such as university hospitals put their efforts into providing benefits for the community and the society at large. Hence, others-benefit appeals might be more persuasive in influencing altruistic motives than self-benefit appeals for university hospitals' (vs. pharmaceutical companies') request for personal information. Given university hospitals' not-for-profit status, the message appeal is in harmony with individuals' attributed motives. This should strengthen individuals' attributions of altruistic motives and might thus have a positive indirect effect on individuals' self-disclosure intentions of personal information.

Hypothesis 3a *The message appeal moderates the relationship between the type of information requester and self-disclosure intentions via altruistic motives, such that the indirect effect will be stronger for the others-benefit (vs. self-benefit) message appeal.*

Egoistic motive attributions play an important role for the association with falsification intentions, particularly when pharmaceutical companies request personal information. They are at least partly governed by the rules of the capital market. Even though they operate to increase overall societal well-being, they simultaneously need to maintain attractiveness to owners and potential investors. It is expected that differences in message appeal (others' vs. self-benefit) influence the relationship between the type of requester of personal information and the intentions to disclose true information via egoistic motive perception. Based on Forehand and Grier's (2003) work, who showed that egoistic attributions only lowered firm evaluations when they were inconsistent with the firm's publicly expressed motive, one can assume that a for-profit healthcare organization that sends an others-benefit message might cause suspicion about the underlying intent of the message. The argument is supported by findings from Becker-Olsen et al. (2006), who found that the fit between what the company stands for and what communication content it uses is important. The persuasiveness of the message is likely to be diminished and consumers are more likely to infer ulterior motives when there is a lack of fit (here: between company goals and communication appeals). Therefore, this thesis assumes that the indirect effect on falsification intentions will be higher for others- (vs. self-) benefit message appeals when pharmaceutical companies (vs. university hospitals) request personal information.

Hypothesis 3b *The message appeal moderates the relationship between the type of information requester and falsification intentions via egoistic motives, such that the indirect effect will be stronger for the others-benefit (vs. self-benefit) message appeal.*

Message Endorser Characteristics: Highly vs. Less Credible Endorsers

Marketing research has shown that celebrity endorsements are highly effective for corporates' communication activities (Bergkvist & Zhou, 2016), and previous research has identified source credibility in particular as a key construct for persuasion (Alcañiz et al., 2010; Goldsmith et al., 2000; Ohanian, 1990). Source credibility has two components: expertise and trustworthiness (Pornpitakpan, 2004). Expertise reflects the extent to which a source is perceived as being knowledgeable about a topic; trustworthiness refers to the honesty of the source (Goldsmith et al., 2000). Messages delivered or endorsed by a credible source were found to be more readily accepted than messages delivered or endorsed by a less credible source (Eisend & Langner, 2010; Rossiter & Smidts, 2012).

Applied to the context of the present study, a highly (versus less) credible endorser who emphasizes the importance of data collection can be assumed to strengthen the positive effect of attributed altruistic motives on individuals' self-disclosure intentions. As an example, a government spokesperson with decision-making power in public health might influence whether and when individuals share true personal information with a health organization for research purposes. Since individuals respond more positively when altruistic motives are paired with high-credibility endorsers (Chan & Zhang, 2019), it can be assume that the indirect effect of the type of information requester on intentions to self-disclose personal information via altruistic motives will be affected by whether a highly (versus less) credible public person endorses the message for the request.

Hypothesis 4a *The message endorser moderates the relationship between the type of information requester and individuals' self-disclosure intentions via altruistic motives, such that the indirect effect will be stronger when a highly (vs. less) credible public person endorses the requesting health organization's efforts in data collection.*

In addition to the facilitating role in influencing self-disclosure intentions, the credibility of an endorser might also influence the relationship between egoistic motives and intentions to falsify personal information. Individuals may contest the source of a message when individuals dismiss the credibility of the endorser (Fransen et al., 2015). This response to reduce or counter persuasion attempts is known as source derogation. Consequently, if a less credible endorser with decision-making power in the government emphasizes a health organizations' efforts of data collection, the relationship between egoistic motives and falsification intentions might be stronger than for a highly credible endorser.

Hypothesis 4b *The message endorser moderates the relationship between the type of information requester and individuals' falsification intentions via egoistic motives, such that the indirect effect will be stronger when a less (vs. highly) credible public person endorses the requesting health organization's efforts in data collection.*

Having explored relevant concepts for consumers' contribution to AI input in this section, the next section elaborates on consumers' role regarding Donabedian's output component of quality assessment. Approaching the second research question that motivates this thesis, it explores how the integration of AI in the healthcare process affects patient-relevant outcome measures. Since consumers' responses to the implementation of AI applications in healthcare are an important quality indicator for AI in healthcare, this thesis investigates individuals' compliance intentions with medical recommendations as one examples of a patient-relevant measure that evaluates the output component of AI. More specifically, this thesis aims to investigate if AI's involvement in the diagnostic assessment affects individuals' compliance intentions with a medical recommendation, as an expression of consumers' quality evaluation of AI output.

3.3. AI Output: Determinants of Consumers' Receptivity of AI Recommendations

The evaluation of the output of an AI application from the perspective of consumers is a quality indicator related to patient-centeredness. It is common practice that individuals seek the advice of experts when they need to decide on how to improve their health. Traditionally, individuals in industrialized countries rely on the medical advice of a human physician. The prevailing information and power asymmetries that exist between the patient and the provider make it difficult for patients to ascertain the type of service they require or judge its quality (Agarwal et al., 2020). This can lead to adverse effects such as unintended over-provision of services or simply a lack of quality by neglecting patients' preferences (Agarwal et al., 2020; Porter & Kaplan, 2016).

Thus, to achieve high quality health services that are patient-centered, it is important to include quality measures that reflect patients' experiences and satisfaction with the service. Patients' quality perceptions can be assessed, for example, via patient satisfaction, adherence and compliance intentions or medical recommendation acceptance (Kruk et al., 2018; Ong et al., 1995; World Health Organization, 2018b). Perceptions of quality, such as confidence in and satisfaction with the health service, can lead to positive health outcomes (Barbosa et al., 2012) and affect individuals' decisions of when and where to seek care (Kruk et al., 2018; Laugese et al., 2015). A positive experience and evaluation of the service quality can improve care utilization, retention and adherence, which lead to better health (Kruk et al. 2018).

The following sections will discuss in more detail factors that influence consumers' acceptance of medical recommendations including AI's involvement in the diagnostic method, disease severity, social presence and innovativeness.

The Role of AI's Involvement in the Diagnostic Method

Patients can directly or indirectly encounter AI in various levels of interaction throughout the whole care delivery. For example, algorithms can process medical data and apply the same rationale as a physician. Thus, AI is able to directly support individuals in health-related questions. Such information technology systems have been found to make medical decision-making more effective and accurate. So far, they have mainly been used as decision support systems that aid physicians during their decision-making process. Pezzo and Pezzo (2006) found that patients evaluated physicians' diagnoses more favorably when they followed a diagnostic decision aid. However, patients' responses to direct interaction with algorithmic recommendations are mixed. Individuals were less likely to follow a medical recommendation when it came from an algorithm than from a physician (Longoni et al., 2019; Promberger & Baron, 2006). Although algorithmic judgment was found to outperform human experts in various contexts, decision-makers are often averse to rely on algorithmic advice in favor of less accurate human judgments (Dietvorst et al., 2018). In their evaluation of algorithmic recommendations, as compared to human ones, individuals tend to weigh certain criteria more heavily. In terms of accuracy, algorithmic recommendations are more likely than humans to be rejected when they make mistakes. More specifically, Dietvorst et al.

(2015) found that even though individuals are aware of the superior performance of algorithms, they are less likely to choose algorithmic advice over human advice. This is because after seeing them both make the same mistake, individuals lose confidence in the algorithm-based advice more quickly than in humans (Dietvorst et al., 2015). In contrast to these findings, other research has indicated that in some instances, individuals rely too much on algorithmic advice, even if the recommendation is inferior. This over-dependence occurs when consumers perceive that algorithms hold comparatively greater domain expertise (Banker & Khetani, 2019). Furthermore, individuals prefer human advice because they subjectively feel that it is easier to understand (despite the importance of accuracy, which might be higher in the case of algorithmic advice) (Yeomans et al., 2019). Individuals may also prefer human advice because it is easier for individuals to shift responsibility to other humans (vs. technology) (Promberger & Baron, 2006; Shaffer et al., 2013). Thus, it makes sense that superior performance was found to be an insufficient criterion for creating a preference for algorithms over humans (Castelo et al., 2019). Longoni et al. (2019) documented individuals' resistance to algorithmic advice across a variety of medical decisions. They showed that individuals' concern about uniqueness neglect explains the preference for a human provider over an automated provider (Longoni et al., 2019). Thus, individuals believe that the consideration of the uniqueness of their case is a fundamental human characteristic that an automated provider lacks.

Even though previous studies have described and explained individuals' aversion to taking advice from algorithms with regard to medical decision-making, recent research takes a more nuanced perspective. In several experiments, Logg et al. (2019) showed that laypeople readily relied on algorithmic advice (e.g., when making visual estimates and when predicting the popularity of songs). However, this was not uniform across all individuals. Participants with expertise in forecasting were less likely to accept algorithmic advice (Logg et al., 2019). Individuals were also found to be more likely to trust and rely on algorithmic recommendations for objective, analytical tasks compared to subjective tasks (Castelo et al., 2019; Yeomans et al., 2019). There is disagreement in the literature about the acceptance of AI in support of physician decision-making. Results showed that the combination of human and algorithmic expertise seems to increase the acceptance of AI as long as it does not replace expert judgment (Palmeira & Spassova, 2015). Pezzo and Pezzo (2006) found that patients evaluated a physician's malpractice case more favorably when the physician used a diagnostic decision aid to make the diagnosis compared to a situation in which no such aid was used. In contrast, Shaffer et al. (2013) demonstrated that clinicians using a computerized decision aid for their diagnosis were perceived more negatively that physicians making an unaided diagnosis. This is in line with results from Arkes et al. (2007) who found that respondents derogated the diagnostic ability of physicians who used a computer-based decision support. Therefore, it can be assumed that there is a difference in individuals' intention to accept a medical recommendation depending on the type expert providing the medical advice.

The Role of Disease Severity

Besides the type of expert providing the medical recommendation, the state of individuals health condition is another factor likely to influence their compliance intentions. When patients are skeptical about using a computer-generated algorithm for decision making (Dietvorst et al., 2015) this skepticism might make individuals less likely to follow a treatment recommendation when no human expert (e.g. a physician) is involved in the medical recommendation process. However, the capability of AI to evaluate and learn from big datasets and then solve medical problems might contribute to the belief that algorithms have greater domain expertise (Banker &

Khetani, 2019). This perception might be more relevant to individuals who have severe health issues. Patients with more severe illnesses tend to delegate decision-making to their physicians (Arora & McHorney, 2000; Levinson et al., 2005). This involves decisions that require medical knowledge and clinical expertise (Thompson et al., 1993). Facing difficult decisions, they seek out state-of-the-art knowledge to make the best medical decision together with their healthcare provider (Gino & Moore, 2007). Since algorithms are especially trusted to perform objective tasks, due to their ability to solve analytical problems with high accuracy, these individuals might consider them as part of their rational decision-making (Castelo et al., 2019). That, in turn, might make individuals less resistant to algorithmic-based recommendations. It is essential for these individuals to base their decisions on well-founded and accurate information. To assist them in making the best decision, individuals likely seek expert advice and information based on state-of-the-art scientific knowledge to support their decision (Gino & Moore, 2007). For individuals who do not face severe health issues, advice from algorithms might be less relevant.

The Role of Social Presence and Innovativeness

The type of expert as well as the level of disease severity are important factors that affect consumers' acceptance of and adherence to recommendations. Beyond that, in the conventional physician-patient relationship, individuals' perceived quality of the medical service encounter as well as patients' level of satisfaction, drive adherence, compliance and persistence with treatment recommendations (Barbosa et al., 2012). Patient satisfaction can be measured based on several dimensions of the health service including accessibility and convenience, financial aspects, technical quality, communication and interpersonal manners (Marshall & Hays, 1994; Ware et al., 1983). These dimensions are similar to the functional, relational and socio-emotional dimensions suggested by Wirtz et al. (2018) that determine the acceptance of AI in service settings. Prior consumer research on technology acceptance has mainly focused on the assessment of the functional dimension (e.g. usefulness, ease of use, performance expectancy) based on well-established models such as the technology acceptance model (TAM) (Davis, 1989) or the united theory of acceptance and use of technology (UTAUT) (Venkatesh et al. (2003). But the question of whether an individual complies with a medical recommendation is determined by both socioemotional and functional elements of a medical assessment (Gino & Moore, 2007; White, 2005).

Social Presence. Besides its functional qualities, health service delivery is also characterized by emotional and social components (Stock & Merkle, 2018). Consequently, when consumers directly interact with AI health services, they will also evaluate their ability to deliver emotional and social value. Socio-emotional elements such as perceived humanness, social interactivity or social presence can positively affect acceptance, service satisfaction (Heerink et al., 2010; van Doorn et al., 2016) and well-being (Sambo et al., 2010). Research on relational elements in health service delivery shows a positive effect on patient health outcomes by increasing individuals' willingness to accept expert advice (White, 2005) and patients' overall satisfaction, compliance and adherence (Hojat et al., 2011; Hojat et al., 2010; Kardas et al., 2013). Specifically, social presence was found to influence attitudes and trust towards technology as well as several important functional technology acceptance variables, such as usefulness or enjoyment (Gefen et al., 2003; Hassanein & Head, 2007). Social presence refers to the extent to which an individual perceives that a social element is present (Short et al., 1976). Social presence theory postulates that different communications media can be classified according to their social presence—an indicator of the degree of awareness of another person within the interaction—and that social presence influences the quality of the interaction (Xin et al., 2015). High social presence creates the sense of a personal, sociable and sensitive being (Lankton et al., 2015). This assigns intimacy to the interaction which facilitates the information interchange between exchanging actors (Li, 2012). This is not limited to interactions between human beings, but can also include computer-mediated communication (Biocca et al., 2003). In general, individuals are more likely to accept algorithmic advice for objective tasks that are numerical and/or analytical in nature. This is grounded in individuals' belief that computers lack the abilities required to perform subjective, i.e. emotional and/or intuitive tasks. Based on the reciprocal nature of a patient's interaction with a physician, social presence should be higher when a human provider (with or without the aid of technology) provides the medical service as compared to an automated provider. Social presence was found to positively affect health outcomes (Sambo et al., 2010). Thus, perception of someone being present or taking care of the patient can then be assumed to positively influence an individual's intention to comply with a medical recommendation.

Innovativeness. The evaluation of the functional performance of the medical assessment is another determinant of compliance with a medical recommendation. It is often difficult for individuals to judge the performance of a healthcare provider due to knowledge asymmetries between them and the providers (Gafni et al., 1998). The use of technology in the medical assessment might indicate to patients that state-of-the-art technology is being utilized and can serve as an indicator for the level of innovativeness in the delivery of the medical service (Fichman et al., 2014). Innovativeness serves as a proxy for newness and, in the medical field, for the consideration of the latest scientific knowledge. Individuals associate innovative technology with success and advancement (Elsbach & Stigliani, 2019). This association prompts individuals to evaluate new technology performance favorably (Clark et al., 2016). An individual's perception of the innovativeness of a diagnostic method should be higher when AI is used because AI can apply recent scientific knowledge with the support of information technology and reliance on big healthcare data (with or without the involvement of physicians). An individual's intention to comply with a recommendation might increase because he or she may feel that the recommendation is based on state-of-the-art scientific evidence. The downstream effects of both social presence and perceived innovativeness are postulated to affect an individual's willingness to comply with a medical recommendation for the treatment.

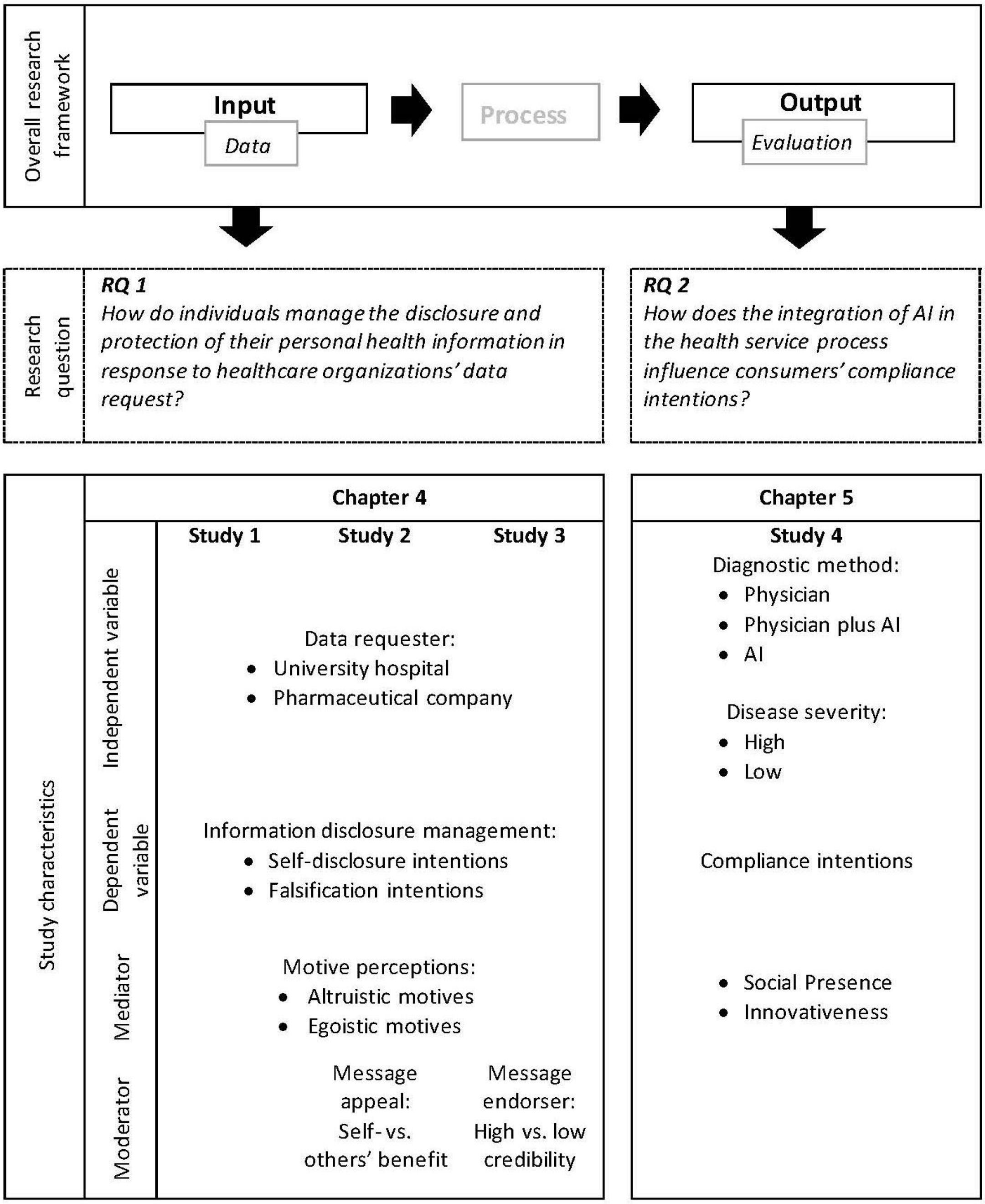
With few exceptions (Promberger & Baron, 2006), there is little data on the general mechanism that affects whether patients comply with recommendations depending on the use of AI technology and the level of human involvement in the medical assessment. Previous studies solely compared two conditions: physician vs. AI or physician vs. physician supported by AI. However, so far, no study has contrasted all three forms of diagnostic methods in one study. Furthermore, the question of whether the severity of the disease has a differential effect on behavioral intentions to comply with the treatment recommendation depending on the type of diagnostic method involved has not yet been fully explored. The present thesis aims to partially fill this gap. Motivated by research question two this thesis explored whether individuals are more likely to follow a recommendation when a physician used AI to derive a diagnosis and give a treatment recommendation as compared to situations in which the physician did not use any AI or when AI fully replaced the physician.

Figure 6 provides an overview of the relevant constructs introduced in this chapter and their contribution to answering the two research questions through four empirical studies. It presents the research framework that guides the following chapters.

Chapter 4 considers the input factor of AI value creation and presents empirical evidence for research question one. It encompasses three empirical studies that subsequently test the hypothesis formulated in Chapter 3.2. Chapter 4 sequentially introduces and presents the methods and results of Study 1-3. The chapter concludes with a general discussion of the findings and illustrates the limitations and opportunities for future research.

Chapter 5 addresses research question two, which is linked to the output of AI value creation. One empirical study explores how the factors introduced in Chapter 3.3 impact consumers' responses to the integration of AI in the healthcare process. Chapter 5 describes the method and results of Study 4 and gives an overview of implications and limitations.

Figure 6 *Overview Research Framework*



Notes: Own illustration

4. Motive Perception Pathways to the Release of Personal Information to Healthcare Organizations

Healthcare experiences a paradigm shift – from reactive care to preventive, value-based care, and from one-size-fits-all medicine to precision medicine (Agarwal et al., 2020). Because of recent advances in technology, the healthcare system produces a vast amount of data. The availability of data types includes behavioral, biological, medical and environmental data, which are collected through diverse sources (e.g., wearables, medical devices, EHR and social media). Given the availability of these data, it is not surprising that big data has become the main driving force for the transformation of the healthcare industry. The human capability alone to analyze such data has reached its limits. This paves the way for technological assistance. Breakthroughs in algorithmic methods such as machine learning and deep-learning-based AI have helped to unlock the potential of big data for healthcare analytics (Choi et al., 2016; Esteva et al., 2019; Haenssle et al., 2018).

AI could play important role in addressing the deficiencies of the healthcare system. In particular, it can increase the speed and reduce the costs of high-quality health care (Bardhan et al., 2020; Cassel & Bindman, 2019). The potential of AI applications is substantial since it can create value for patients, clinicians, healthcare organizations, pharmaceutical companies and health insurers, among others. Yet the key to creating beneficial AI applications strongly depends on the quality and quantity of relevant health data (Wallis, 2019).

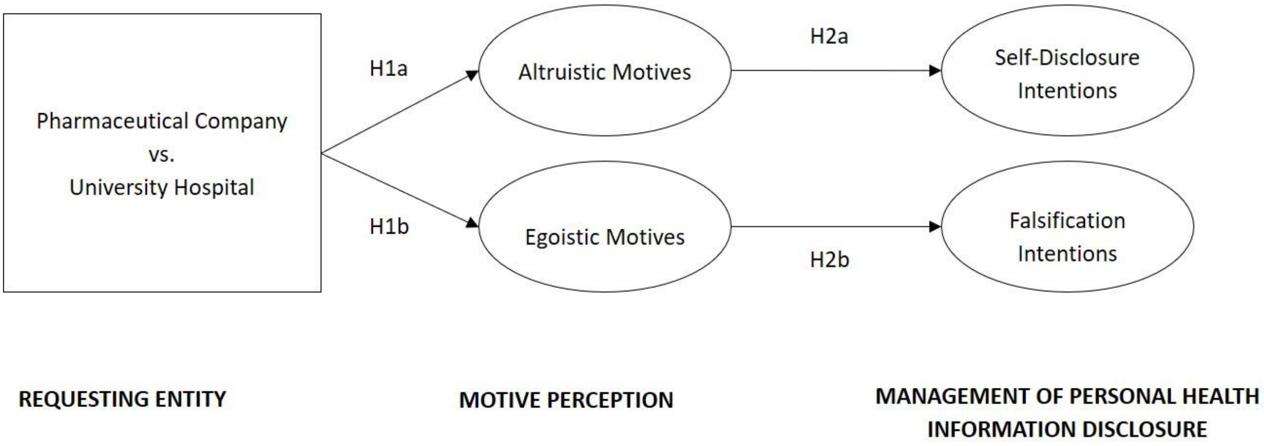
The data need to be disclosed and they have to be valid and reliable (if made available). Prior research on whether and when individuals disclose personal information has studied various factors that facilitate or harm data sharing (Jiang et al., 2013; Kehr et al., 2015; White, 2004; Zhang et al., 2018), but has rarely looked at who requests the data. This thesis argues that the entity that requests personal information from individuals influences their likelihood to disclose data. This is because individuals attribute motives to the various requesting entities (particularly for-profit organizations vs. not-for-profit organizations) with different consequences on intentions to disclose. Beside the resulting consequences of who the entities are that request information, this research explores when and how entities may increase the likelihood that the request is successful. The latter is particularly important to for-profit organizations such as pharmaceutical companies that can use such data to improve their products and services and innovate to increase profits and satisfy shareholders (Schneider, 2018; Smalley, 2017).

The remaining chapter is divided into three sections that describe the empirical studies (Study 1-3), which were conducted to answer the research question one. Each chapter comprises an introduction of the applied methodology and a presentation of the results. The chapter concludes with a general discussion of the findings of all three studies and illustrates the limitations and opportunities for future research.

4.1 Study 1 – Motive Perceptions

The purpose of Study 1 was to provide initial evidence that individuals make different motive attributions to not-for-profit (vs. for-profit) healthcare organizations' requests to share certain personal information with them. Moreover, the study assessed whether attributed altruistic and egoistic motives mediate the relationship between the type of information requester and individuals' intentions to self-disclose or falsify personal information. Figure 7 provides an overview of the conceptual model that guided the research in Study 1.

Figure 7 *Conceptual Model (Study 1)*



4.1.1. Methods

Design and Sample

This study conducted a scenario-based, randomized experimental design. The information requester was manipulated between participants, being either a university hospital (as an example of a not-for-profit organization) or a pharmaceutical company (as an example of a for-profit organization). Covid-19 was used as the research context for the study.

A total of 204 respondents recruited from Amazon's Mechanical Turk (an online platform via which registered individuals complete tasks in return for small payments) participated in Study 1, which was conducted on April 6, 2020. Most of them were male (68.6%). Participants were between 21 to 68 years old with a mean age of 36.2 years and 55.9% had a Bachelor's degree. Most of the participants either lived in three-person (28.4%) or four-person (29.9%) households. General health was assessed on a 5-point scale, ranging from poor (1) to excellent (5). Participants stated that they are in good health (*M* = 3.82, *SD* = .88). At the time, about 77.5% of the respondents had not been tested for Covid-19, neither had their families (73.0%). The majority of respondents (91.1%), as well as their families (88.7%), had not been infected with Covid-19.

Participants' estimated their risk of being infected with the virus on a seven-point rating scale as rather moderate ($M = 4.62$, $SD = 1.72$). Also, participants perceived the risk of Covid-19 affecting their health as moderate ($M = 4.82$, $SD = 1.74$).

Table 8 *Sample Characteristics (Study 1)*

Gender	Sample (%)	Age	Sample (%)	General health	Sample (%)	Household size	Sample (%)
Female	31.4	18-25	11.8	Poor	1.0	1 person	14.7
Male	68.6	26-35	48.5	Fair	5.4	2 persons	19.1
		36-45	19.6	Good	27.0	3 persons	28.4
		46-55	11.3	Very good	43.6	4 persons	29.9
		56-65	7.4	Excellent	23.0	>4 persons	7.8
		>65	1.5				
Education	**Sample (%)**	**Tested COVID**	**Sample (%)**	**Infected COVID**	**Sample (%)**		
High school	11.3	Self		Self			
Some college	18.1	Yes	22.5	Yes	8.9		
Bachelor's degree	55.9	No	77.5	No	91.1		
Master's degree	12.7	Family		Family			
Professional degree	1.5	Yes	27.0	Yes	11.3		
Doctorate	0.5	No	73.0	No	88.7		

Procedure

After giving consent to participation, participants were asked to picture themselves in a hypothetical scenario. Participants were randomly assigned to one of the two experimental conditions. They either read that given the current situation with the Covid-19 virus, a university hospital announced that they are setting up a comprehensive database of people's health data, or they read that given the current situation with the Covid-19 virus, a pharmaceutical company announced that they are setting up a comprehensive database of people's health data. They were also given information about the aim of the database and the organization's call on the general population to contribute to this database (which was kept identical between the experimental conditions). Participants were subsequently told to access a secure website where they would be asked about what kind of data they would be willing to provide (Appendix A).

After reading the scenario, participants completed a questionnaire. They answered questions about the perceived motives of the healthcare organization for the information request and about their self-disclosure and falsification intentions. The survey ended with several demographics and descriptive variables.

Variables

Self-disclosure intentions were operationalized as to the extent to which individuals were willing to reveal 20 different types of personal information (Cronbach's alpha = .94). The variables were adopted from previous research (Mothersbaugh et al., 2012) and adapted to the context of the study (Appendix B). The items were measured on a seven-point scale, with response options ranging from 1 = very unlikely to 7= very likely.

Falsification intentions were operationalized as the likelihood of individuals to provide false personal information to the information requester (Cronbach's alpha = .90). This study measured the construct on a four-item, seven-point rating scale (1 = strongly disagree, 7 = strongly agree), adopted from previous research (Lwin et al., 2007; Martin et al., 2017) and adapted to the study's context (Appendix B).

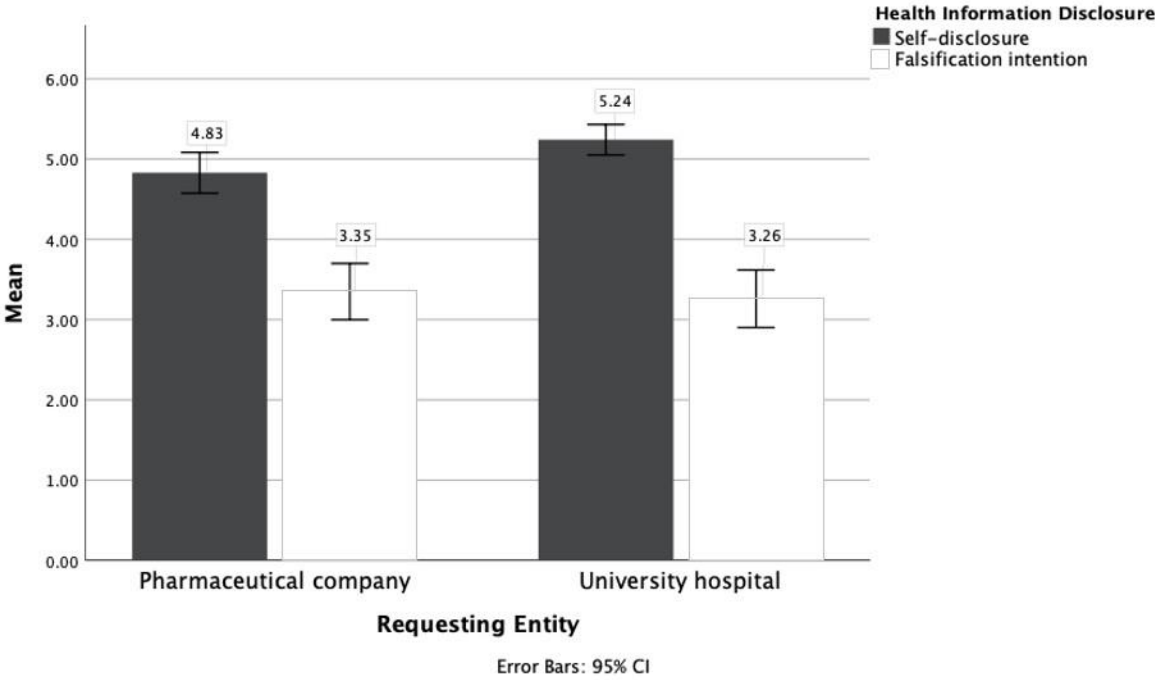
Perceived motives were operationalized as a bi-dimensional construct composed of *altruistic* and *egoistic motives* (Appendix C). Altruistic attributions reflect an organization's consideration of the well-being of individuals as the underlying motivation (Cronbach's alpha = .93), whereas egoistic attributions focused on firm-centered motives (Cronbach's alpha = .85). Both attributed motives were measured on a seven-point rating scale (1 = strongly disagree, 7 = strongly agree). The altruistic motive construct included eight items and the egoistic motives included six items (Ellen et al., 2006; Vlachos et al., 2009).

4.1.2. Results and Discussion

A path model (Mplus) was used to test the hypotheses. The model included the type of information requester (pharmaceutical company = 1, university hospital = 0), egoistic and altruistic motives as parallel mediators, and self-disclosure and falsification intentions as the dependent variables. All direct and indirect paths were included in the model.

The model explained 42.6% of the variance in self-disclosing intentions and 23.5% of the variance in falsification intentions. Figure 8 displays the mean scores of individuals' intention to disclose or falsify the requested information for each requesting entity. It shows that overall individuals' intentions to disclose information truthfully were higher than to falsify them. Intentions to disclose information were higher when a university hospital requested the data than when a pharmaceutical company makes the request. In contrast, intentions to falsify information were comparable for both requesting entities.

Figure 8 *Means and 95% Confidence Intervals for Self-disclosure and Falsification Intentions for the Two Requesting Entities (Study 1)*



The results showed that the pharmaceutical company was attributed with lower altruistic motives (*ß* = -.35, *SE* = .17, *p* = .04) and higher egoistic motives (*ß* = .39, *SE* = .17, *p* = .03) compared to the university hospital, supporting H1a and H1b. Furthermore, the path coefficient between altruistic motives and self-disclosure intentions was positive (*ß* = .61, *SE* = .07, *p* < .001), providing initial support for H2a. There was no significant effect of egoistic motives on self-disclosure intentions (*ß* = .07, *SE* = .06, *p* = .23). The path coefficient between egoistic motives and falsification intentions was positive (*ß* = .73, *SE* = .09, *p* < .001), providing initial support for H2b. There was no significant effect of altruistic motives on falsification intentions (*ß* = .08, *SE* = .13, *p* = .52).

To test the postulated mediation effect (H2a and H2b), this study considered the indirect effects of the type of information requester via egoistic and altruistic motives on the two types of disclosure management. For self-disclosure intentions, there was a significant indirect negative effect of the type of information requester via altruistic motives (*ß* = -.21, *CI 95%* [-.40; -.05]). There was no significant indirect effect via egoistic motives (*ß* = .03, *CI 95%* [-.00; .09]). There is evidence for a full mediation via altruistic motives, because the direct effect of the type of information requester was not significant (*ß* = -.23, *p* = .06). The results thus support H2a.

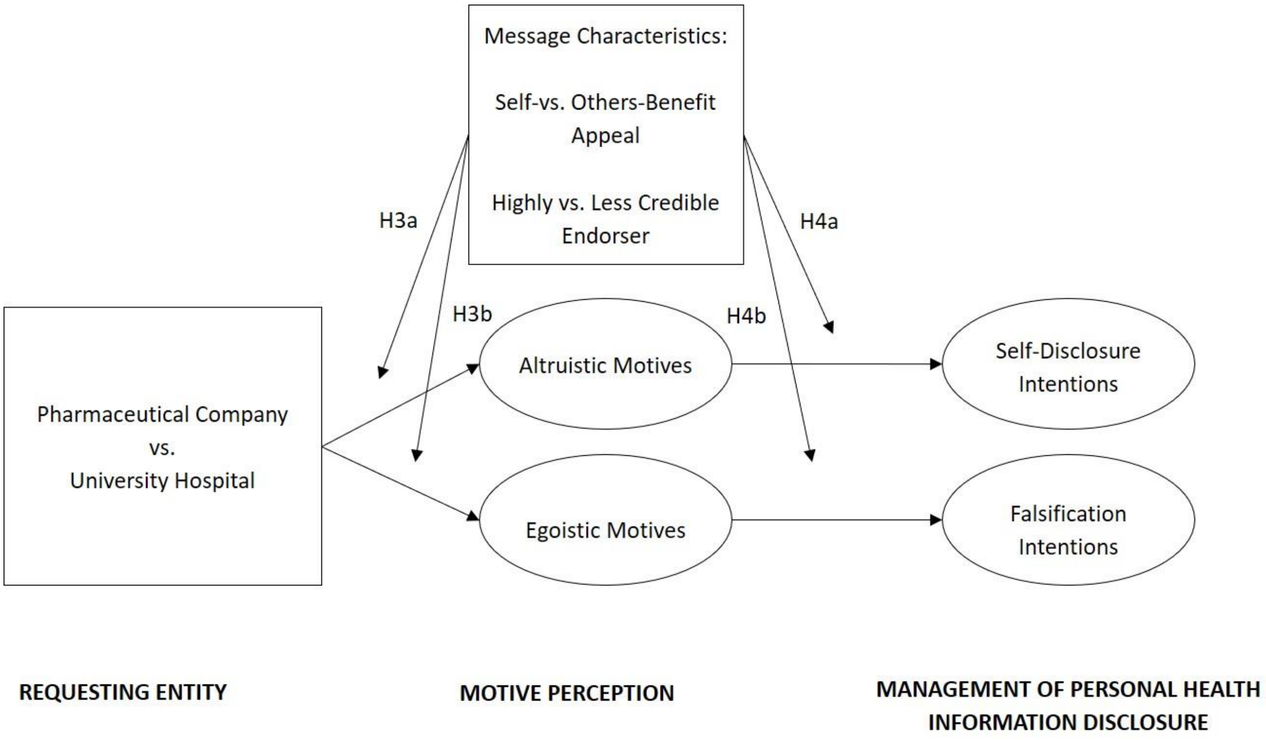
For falsification intentions, egoistic motives (*ß* = .28, *CI 95%* [.07; .49]), but not altruistic motives (*ß* = -.03, *CI 95%* [-.17; .02]), had a mediating effect. There was no direct effect of the requesting stakeholder on falsification intentions (*ß* = -.16, *p* = .47). The results thus provide evidence of full mediation and support H2b.

In summary, the results showed that individuals attribute different motives to healthcare organizations when they request personal information. While university hospitals are attributed with the positively connoted motive of altruism, pharmaceutical companies are perceived as egoistically motivated (with negative consequences). The results further indicated distinct downstream effects of attributed motives. On the one hand, individuals were more willing to disclose their data if they perceived that the requesting organization is acting based on altruistic motives (i.e., the motive functions as gate openers). On the other hand, individuals were more likely to protect their data by intending to provide false information when they perceived egoistic motives to be the main driver for the organization requesting their data (i.e., the motive functions as a privacy protection tool). The research thus extends previous insights into the differential consequences of altruistic versus egoistic motives, highlighting not only the positive versus negative downstream effects (Barone et al., 2007; Woisetschläger et al., 2017), but that different disclosure management tactics are associated with the two motives: self-disclosure with altruism and falsification with egoism.

Study 1 focused on the question of how different requesters for personal information make individuals more or less likely to share true information about them and their health. The study did not consider potential moderators that could explain when the two requesters under consideration can profit (or are harmed) by the motive pathways to self-disclose or falsify personal information. The next section considers two potential moderators: message appeal (considered in Study 2) and message endorser (considered in Study 3; see Figure 9).

4.2. Study 2 – Message Appeal

Figure 9 *Conceptual Model (Study 2 and 3)*



The purpose of Study 2 is to assess whether message appeal – the focus on others' benefits versus self-benefits in communication campaigns about the release of personal information –

influences the two pathways of how individuals self-disclose or falsify information depending on who requests the data. This thesis expects that who the requester is matters more when others' benefits (vs. self-benefits) are highlighted.

4.2.1. Methods

Design and Sample

A 2 (information requester: pharmaceutical company vs. university hospital) by 2 (message appeal: self-benefit vs. others-benefit) design was used, manipulating both factors between participants. The study was conducted on May 5, 2020, and used the same scenario as in Study 1. A total of 330 participants from the US (M_{age}: 38.8 years, 65.2% males) were recruited from Amazon's Mechanical Turk and they were randomly assigned to one of four experimental groups. Because of the large impact of the pandemic in the US, participants who stated that they or somebody from their family had been infected were excluded for subsequent analysis. Participants stated that they are in good health (M = 3.79, SD = .92). The estimated risk of being infected with Covid-19 (M = 4.23, SD = 1.75) and the perceived risk of Covid-19 affecting health (M = 4.61, SD = 1.68) were perceived as moderate.

Table 9 *Sample Characteristics (Study 2)*

Gender	Sample (%)	Age	Sample (%)	General health	Sample (%)
Female	34.5	18-25	11.8	Poor	1.0
Male	65.2	26-35	48.5	Fair	5.4
		36-45	19.6	Good	27.0
		46-55	11.3	Very good	43.6
		56-65	7.4	Excellent	23.0
		>65	1.5		
Household size	**Sample (%)**	**Education**	**Sample (%)**		
1 person	14.2	High school	7.0		
2 persons	17.6	Some college	12.7		
3 persons	27.0	Bachelor's degree	48.5		
4 persons	30.0	Master's degree	29.4		
>4 persons	11.2	Professional degree	1.5		
		Doctorate	0.9		

Procedure

Participants read that a university hospital (or a pharmaceutical company) announced that they are setting up a comprehensive database of people's health data (Appendix A). After the healthcare organization's call on the general population to contribute to this database, participants read an announcement with one of the two different message appeals (Appendix D). Participants subsequently followed the same procedure as in Study 1.

Variables

Study 2 used the same scales as in Study 1 to assess individuals' self-disclosures (Cronbach's alpha = .96) and falsification intentions (Cronbach's alpha = .90) as well as attributions of egoistic (Cronbach's alpha = .86) and altruistic motives (Cronbach's alpha = .93).

4.2.2. Results and Discussion

Following Stride et al.'s (2015) guidelines, a path model was created with two dependent variables, two parallel mediators and one moderator. As in Study 1, the information requester was included as an independent variable (pharmaceutical company = 1, university hospital = 0). The model tests for moderating effects of message appeal (self-benefit = 1, others-benefit = 0) on both independent variable-mediator paths (a paths) and mediator-dependent variable paths (b paths). Attributed egoistic and altruistic motives are modeled as mediators on self-disclosure and falsification intentions as dependent variables.

The model explained 48.2% of the variance in self-disclosing intentions and 15.1% of the variance in falsification intentions. Figure 10 displays the mean scores of individuals' intention to disclose or falsify the requested information for each requesting entity. It shows that overall individuals' intentions to disclose information truthfully were higher than to falsify them. Intentions to disclose information were higher when a university hospital requested the data than when a pharmaceutical company makes the request. In contrast, intentions to falsify information were comparable for both requesting entities.

Figure 10 *Means and 95% Confidence Intervals for Self-disclosure and Falsification Intentions for the Two Requesting Entities (Study 2)*

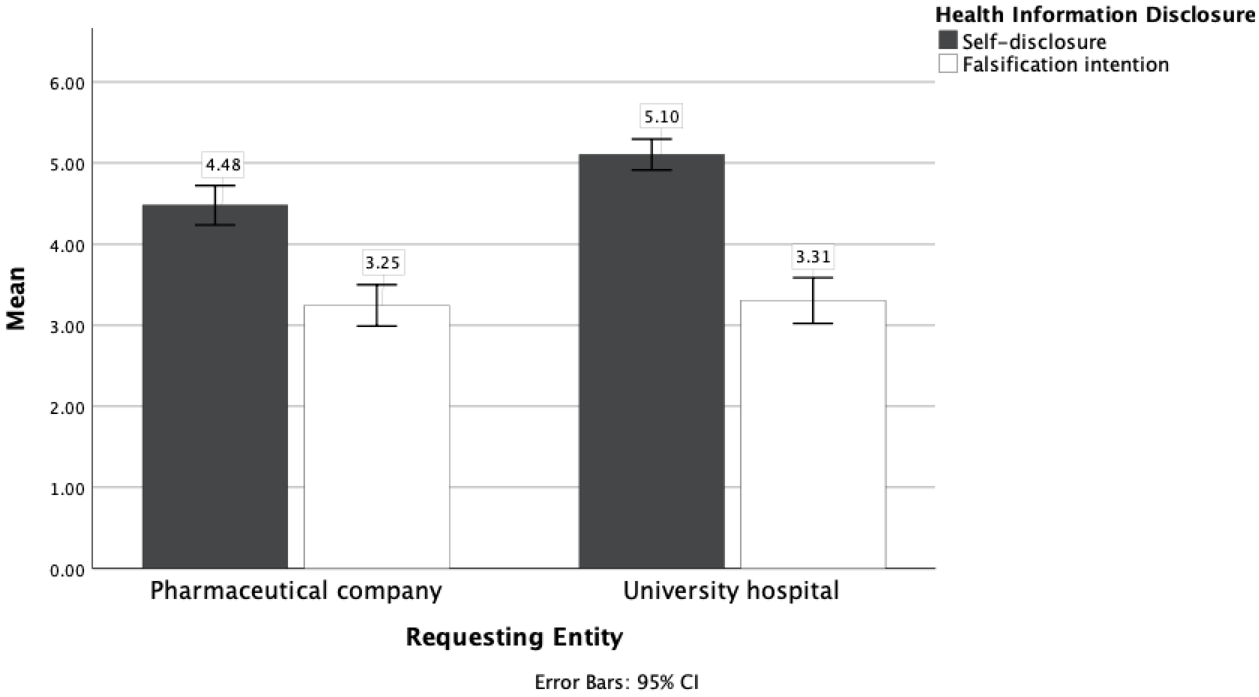


Table 10 provides an overview of the results of the moderated mediation analysis. In support of H1a and H1b, the pharmaceutical company was attributed with lower altruistic motives (*ß* = -.59, *SE* = .19, *p* < .001) and higher egoistic motives (*ß* = .63, *SE* = .18, *p* < .001) compared to the university hospital. The message appeal had no direct effect on attributed motives ($ß_{Egoistic}$ = .29, *SE* = .19, *p* = .14, $ß_{Altruistic}$ = .18, *SE* = .14, *p* = .18). While the interaction effect of the type of requester and message appeal (path a) was significant for egoistic motives (*ß* = -.61, *SE* = .25, *p* = .01), it was non-significant for altruistic motives (*ß* = -.03, *SE* = .25, *p* = .91). In support of H2a and H2b, the path coefficients between altruistic motives and self-disclosure (*ß* = .83, *SE* = .08, *p* = <.001) and between egoistic motives and falsification were significant (*ß* = .57, *SE* = .10, *p* = <.001).

Table 10 *Results of the Moderation Effect of Message Appeal (Study 2)*

Direct effects on motive perception	***B***	***SE***	***p***
Requester → Egoistic motives	.63	.18	< .001
Message appeal → Egoistic motives	.29	.19	.14
Requester × Message appeal → Egoistic motives	-.61	.25	.01
Requester → Altruistic motives	-.59	.19	< .001
Message appeal → Altruistic motives	.18	.14	.18
Requester × Message appeal → Altruistic motives	-.03	.25	.91
Direct effects on self-disclosure and falsification			
Requester → Self-disclosure	-.14	.12	.25
Altruistic motives → Self-disclosure	.83	.08	< .001
Egoistic motives → Self-disclosure	.12	.08	.11
Message appeal → Self-disclosure	-.44	.66	.50
Altruistic motives × Message appeal → Self-disclosure	.08	.11	.49
Egoistic motives × Message appeal → Self-disclosure	-.04	.10	.69
Requester → Falsification	-.33	.19	.08
Altruistic motives → Falsification	-.14	.12	.21
Egoistic motives → Falsification	.57	.10	< .001
Message appeal → Falsification	.10	1.15	.93
Altruistic motives × Message appeal → Falsification	.02	.18	.91
Egoistic motives × Message appeal → Falsification	-.05	.15	.75
Moderation effects of message appeal			
Conditional indirect effect of altruistic motives on self-disclosure	***B***		***CI 95%***
Self-benefit	-.56		[-.84; -.31]
Others-benefit	-.49		[-.73; -.21]
Conditional indirect effect of egoistic motives on self-disclosure			
Self-benefit	.00		[-.02; .05]
Others-benefit	.08		[-.00; .19]
Conditional indirect effect of altruistic motives on falsification			
Self-benefit	.08		[-.06; .22]
Others-benefit	.08		[-.02; .23]
Conditional indirect effect of egoistic motives on falsification			
Self-benefit	.01		[-.14; .15]
Others-benefit	.36		[.19; .59]

Notes. B = Unstandardized path coefficient; *SE* = Standard error; *p* = Significance; CI 95% = 95% Confidence interval. Self-disclosure = Intentions to self-disclose personal information; falsification = Intentions to falsify personal information.

To test H3a and H3b, conditional indirect effects were considered via bootstrapping. The indirect effects of the type of requester on self-disclosure intentions via altruistic motives were negative and significant for both message appeals (*ß*$_{others}$ = -.49, *CI 95%* [-.73; -.21] and *ß*$_{self}$ = -.56, *CI 95%* [-.84; -.31], respectively). The index of moderated mediation, which tests for differences in the two indirect paths, is -.07 with a bootstrap 95% confidence interval of [-.46; .29], indicating that pharmaceutical companies were less likely to successfully request data from individuals via shaping altruistic motive perception for both the others-benefit and the self-benefit message. The results do not support H3a.

The indirect effects of the type of requester on falsification intentions via egoistic motives were non-significant in the self-benefit condition (*ß* = .01, *CI 95%* [-.14; .15]) but positive and significant in the others-benefit condition (*ß* = .36, *CI 95%* [.19; .59]). The index of moderated mediation was -.35 with a bootstrap 95% confidence interval of [-.62; -.13], indicating that pharmaceutical companies were more likely to request falsified data from individuals via shaping egoistic motive perception in the others-benefit (but not in the self-benefit) message appeal condition. The results support H3b. The finding is interesting and reveals the challenges that for-profit healthcare organizations are faced with: given their status, others' benefits might not match with consumer expectations and this likely led to the negative outcomes (Forehand and Grier 2003; here: likelihood to falsify personal information to protect one's privacy but to still be able to interact with the provider).

In summary, the results replicate the findings from Study 1 with regard to H1 and H2. In addition, the study showed that others-benefit message appeals increased the attributions of egoistic motives for pharmaceutical companies (vs. university hospitals), which resulted in higher falsification intentions. There was no differential effect on self-disclosure intentions for the two message appeals. This might be due to the fact that individuals tend to be not only community-oriented but also selfish; self-benefits appeals can be effective too, because the behavior serves their own needs (Fisher et al. 2008).

One limitation of Study 2 is that it considered the message content without reference to a potential message endorser. During the pandemic and for health promotion and disease prevention purposes, actors such as politicians or public health representatives often endorse messages directed at individuals (Bergner et al. 2013, Newton et al. 2015). Such endorsers were found to influence people's pro-social behaviors (Wymer and Drollinger 2014) and might, in the context of the present research, influence how and when intentions to disclose personal information are formed. The following section details how a message endorser might influence individuals' intentions to self-disclose or falsify personal information.

4.3. Study 3 – Message Endorser

The purpose of Study 3 was to assess whether a message endorser's credibility in communication campaigns about the release of personal information influences the two pathways of how individuals self-disclose or falsify information depending on who requests the data. This study expected that a highly credible source strengthens the indirect pathway on intentions to self-disclose personal information, whereas it weakens the indirect pathway to falsify personal information.

4.3.1. Methods

Design and Sample

To test the hypotheses, this study used a 2 (information requester: pharmaceutical company vs. university hospital) by 2 (message endorser's credibility: high vs. low) design, manipulating both factors between participants.

The study took place on May 5, 2020 and participants were only allowed to participate if they had not taken part in Study 2. The same procedure was applied as for Study 2 and a total of

328 Amazon's Mechanical Turk participants from the US (M_{age}: 36.7 years, 64.3% males) were randomly assigned to one of four experimental groups. Participants stated that they are in good health (M = 3.83, SD = .89). Perceived risks of getting infected with the virus (M = 4.01, SD = 1.81) and perceived risks of Covid-19 affecting individuals' health were moderate (M = 4.29, SD = 1.72).

Table 11 *Sample Characteristics (Study 3)*

Gender	Sample (%)	Age	Sample (%)	General health	Sample (%)
Female	35.7	18-25	12.5	Poor	1.2
Male	64.3	26-35	45.4	Fair	7.0
		36-45	19.8	Good	21.0
		46-55	11.0	Very good	49.1
		56-65	10.1	Excellent	21.6
		>65	1.2		

Household size	Sample (%)	Education	Sample (%)
1 person	13.4	High school	6.1
2 persons	21.0	Some college	24.7
3 persons	32.6	Bachelor's degree	51.2
4 persons	25.0	Master's degree	14.9
>4 persons	7.9	Professional degree	2.4
		Doctorate	.6

Procedure

Again, Covid-19 provided the study context. Participants read that a university hospital (or a pharmaceutical company) announced that they are setting up a comprehensive database of people's health data (Appendix A). Following this, participants read that a public person (either

M.D. Deborah Birx or U.S. President Donald Trump) encourages people to provide personal health data to healthcare organizations to support them in their efforts. The public person furthermore highlighted the importance of up-to-date and real health data in a press conference for experts in health and medicine (Appendix E). The study continued and ended as described above.

Deborah Birx was selected as the public person with a presumably high credibility. She is a renowned health official who is responsible for government responses to Covid-19. Donald Trump, on the other hand also works for the government but was found to provide misleading statements about various healthcare topics even before the Covid-19 pandemic (Hatcher, 2019), potentially leading to low-credibility perceptions. More specifically, he has been criticized for the government's slow response to Covid-19 (Pew Research Center, 2020), making the US the country with the highest number of Covid-19 disease-related deaths (John Hopkins Coronavirus Research Center, 2020).

Variables

Study 3 used the same scales as the previous studies to assess individuals' self-disclosures (Cronbach's alpha = .96) and falsification intentions (Cronbach's alpha = .90) as well as attributions of egoistic (Cronbach's alpha = .85) and altruistic motives (Cronbach's alpha = .94). To test whether our assumptions about the selected endorsers were correct or not, we assessed source credibility (Cronbach's alpha = .98) with a 14-item, seven-point rating scale adopted from Ohanian (1990) and Reysen (2005). The study also measured perceived the domain-specific expertise (Cronbach's alpha = .97) of the endorser with regard to Covid-19. To do so, this study adopted five items from Ohanian (1990) and adapted them to the study context (Cronbach's alpha = .97). All items can be seen in Appendix F.

4.3.2. Results

The assumption check about the credibility of the two selected endorsers showed that both credibility (M_{Birx} = 5.14 and M_{Trump} = 3.97, $F(1,326) = 84.37$, $p < .001$) and domain-specific expertise with regard to Covid-19 (M_{Birx} = 5.47 and M_{Trump} = 3.77, $F(1,326) = 145.15$, $p < .001$) differed between the two message endorsers in the expected direction.

Study 3 specified a similar model compared to Study 2, replacing message appeal with message endorser's credibility (low = 1, high = 0). The model explained 52.5% of variance in self-disclosure intentions and 15.9% of variance in falsification intentions. Figure 11 displays the mean scores of individuals' intention to disclose or falsify the requested information for each requesting entity. It shows that overall individuals' intentions to disclose information truthfully were higher than to falsify them. This was the case when a university hospital as well as when a pharmaceutical company requested the data.

Figure 11 *Means and 95% Confidence Intervals for Self-disclosure and Falsification Intentions for the Two Requesting Entities (Study 3)*

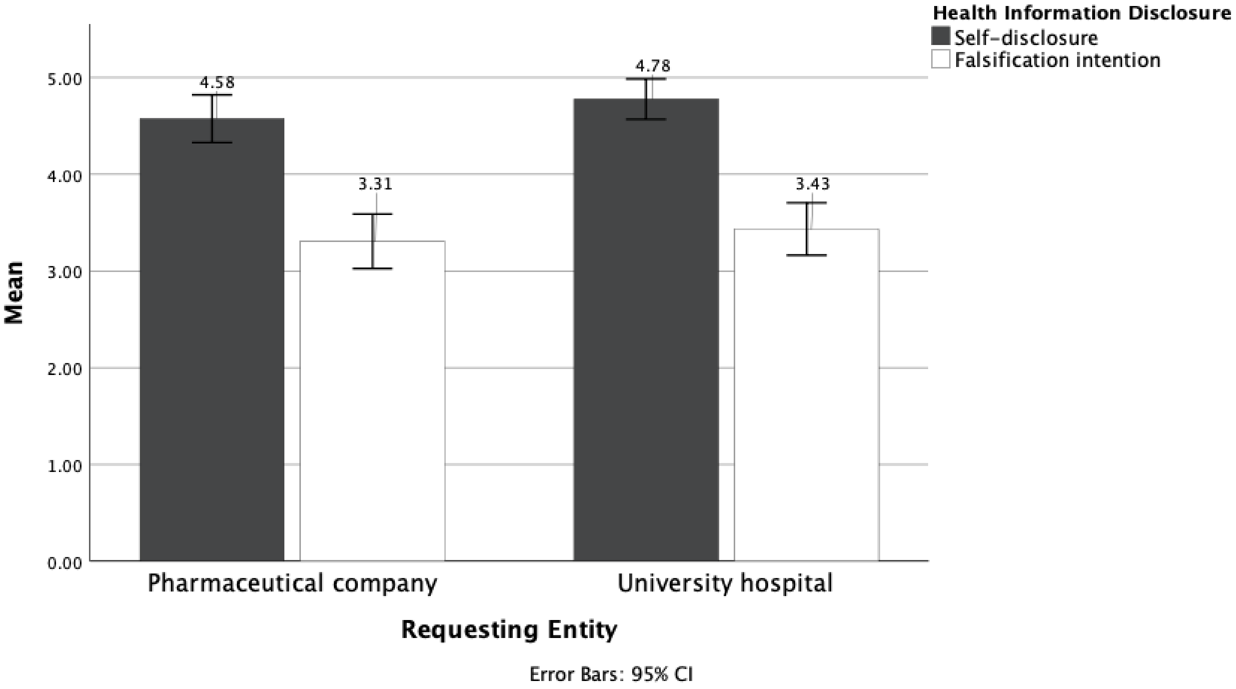


Table 12 provides an overview of the results of the moderated mediation analysis. The pharmaceutical company was attributed with lower altruistic motives (*ß* = -.41*, SE* = .21, *p* = .05) compared to the university hospital. There was a marginal effect on egoistic motives (*ß* = .32, *SE* = .19, *p* = .10). The results thus largely support H1. The path coefficients between altruistic motives and self-disclosure intentions (*ß* = .86, *SE* = .06, *p* <.001) and between egoistic motives and falsification intentions were positive (*ß* = .54, *SE* = .10, *p* <.001), supporting H2.

Table 12 *Results of the Moderation Effect of Message Endorser (Study 3)*

Direct effects on motive perception	***B***	***SE***	***p***
Requester → Altruistic motive	-.41	.21	.05
Endorser → Altruistic motive	-.05	.19	.77
Requester × Endorser → Altruistic motive	.17	.28	.55
Requester→ Egoistic motive	.32	.19	.10
Endorser → Egoistic motive	-.06	.21	.76
Requester × Endorser→ Egoistic motive	.07	.27	.80
Direct effects on self-disclosure and falsification	***B***	***SE***	***p***
Requester→ Self-disclosure	.05	.12	.66
Altruistic motive→ Self-disclosure	.86	.06	< .001
Egoistic motive→ Self-disclosure	-.02	.08	.80
Endorser → Self-disclosure	.02	.63	.98
Altruistic motive × Endorser → Self-disclosure	-.12	.09	.18
Egoistic motive × Endorser → Self-disclosure	.09	.12	.44
Requester→ Falsification	-.34	.19	.07
Altruistic motive→ Falsification	.12	.10	.25
Egoistic motive→ Falsification	.54	.10	< .001
Endorser → Falsification	-.60	.96	.53
Altruistic motive × Endorser → Falsification	-.12	.15	.41
Egoistic motive × Endorser → Falsification	.30	.15	.04
Moderation effects of message endorser			
Conditional indirect effect of altruistic motive on self-disclosure	***B***		***CI 95%***
Low credibility	-.18		[-.45; .05]
High credibility	-.36		[-.68; -.06]
Conditional indirect effect of egoistic motive on self-disclosure			
Low credibility	.03		[-.02; .12]
High credibility	-.01		[-.07; .02]
Conditional indirect effect of altruistic motive on falsification			
Low credibility	.00		[-.04; .06]
High credibility	-.05		[-.18; .01]
Conditional indirect effect of egoistic motive on falsification			
Low credibility	.33		[.09; .61]
High credibility	.17		[.01; .38]

Note: See Table 10 for abbreviations.

The interaction effect of the message endorsers' credibility and egoistic motives on falsification intention was significant (*ß* = .30, *SE* = .15, *p* = .04), while there was no significant interaction effect of message endorsers' credibility and altruistic motives on self-disclosure intentions (*ß* = -.12, *SE* = .09, *p* = .18). When a pharmaceutical company (vs. university hospital) acts as the information requester, the analysis revealed a negative and significant conditional indirect effect in situations of high credibility of the endorser on self-disclosure intentions via altruistic motives (*ß* = -.36, *CI 95%* [-.68; -.06]). There was no such evidence for the low-credibility message endorser (*ß* = -.18, *CI 95%* [-.45; .05]). In the high credibility condition, the indirect effect was present, while it disappeared in the low-credibility condition. Even though these results indicate that university hospitals were more likely to successfully request data from individuals in the high-credibility (but not in the low-credibility) message endorser condition by shaping altruistic motive perception compared to pharmaceutical companies, the index of moderated mediation (.17) was non-significant (bootstrap 95% confidence interval of [-.22; .55]). The results therefore only partly support H4a.

The assessment of the conditional indirect effects of the highly credible endorser on falsification intentions revealed a positive effect (*ß* = .17, *CI 95%* [.01; .38]), which increased in magnitude for the low-credibility endorser (*ß* = .33, *CI 95%* [.09; .61]). The index of moderated mediation was .15 with a bootstrap 95% confidence interval of [-.19; .45]. Even though the results indicate that pharmaceutical companies were more likely to receive falsified data from individuals in the low-credibility (but less so in the high-credibility) message endorser condition by shaping egoistic motive perception, the results only partly support H4b.

The results of Study 3 showed that the credibility of an external message endorser influences how individuals respond to requests from healthcare research entities to disclose true personal information. The study thus identified another moderator of the relationship between the type of information requester and self-disclosure intentions of true personal data (beside message appeal, considered in Study 2). While message appeal interacts with the type of requester and exerts its influence on motive perception, message endorser credibility interacts with the motive perception and exerts its influence on the two outcome variables depending on the perception of these two motives: self-disclosure and falsification intentions of personal information.

4.4. General Discussion of the Results of Studies 1-3

Theoretical and Practical Implications

The purpose of Studies 1-3 was to find out how individuals manage the disclosure of sensitive personal information depending on who requests the data that will be used for healthcare research purposes. With these findings, this thesis contributes to the literature in three ways. (1) it provides implications in reference to both self-disclose and falsification; (2) it introduces motive perception pathways that shape individuals' likelihood to disclose personal information depending on the type of requester (for-profit vs. not-for-profit organizations); and (3) it identifies message appeal and message endorser credibility as important moderators of the relationship between the requesting entity, motive perception and likelihood of disclosure of personal information.

First, this thesis has argued, and provided empirical evidence, that it is important to incorporate both self-disclosure and falsification intentions to fully understand individuals' information management. While prior studies in the healthcare context primarily investigated disclosure and its complement non-disclosure (Anderson & Agarwal, 2011; Bansal et al., 2010; Lin et al., 2016; Zhang et al., 2018), this does not fully reflect on how individuals handle information flows. Such an approach specifies only the amount of data that individuals are willing or not willing to share but disregards the aspect of its accuracy. Other studies addressed this aspect by investigating individuals' misrepresentation intention as a tool to protect personal information (Lwin et al., 2007; Martin et al., 2017; Norberg & Horne, 2013; Youn, 2009). While both streams of research identified important factors that facilitate or inhibit information sharing, a more holistic view on individuals' information management is still lacking. This thesis argues that the amount as well as the accuracy of shared data are factors of information management. For advanced healthcare applications that are based on the latest technology, factors such as variety, quantity and quality of data are key. Therefore, it is essential to determine what prompts individuals to share personal information truthfully and what causes misrepresentation intentions. To address this, this thesis applied a dual approach in this study by incorporating self-disclosure as well as falsification. Thus, this thesis advances the understanding of how individuals govern their personal health information and show that information management goes beyond pure sharing or non-sharing of data.

Second, this thesis found that individuals were more likely to attribute egoistic motives to for-profit organizations than to non-profit healthcare organizations, with differential downstream consequences. To our knowledge, this is the first study that investigated motive attributions in the healthcare setting and information management context. Prior studies mainly investigated individuals' attributed motives for branding purposes, such as for the context of cause-related marketing (Barone et al., 2007), corporate social responsibility (Becker-Olsen et al., 2006; Ellen et al., 2006; Groza et al., 2011) and sponsorship (Rifon et al., 2004; Woisetschläger et al., 2017). The two attributed motives – altruistic and egoistic motives – explain why individuals open or close information boundaries in response to an information request. If individuals perceive egoistic motives driving the information request, they are more likely to provide inaccurate information. Egoistic motives increase the perceived risk of opportunistic behaviors, which increase individuals' vulnerability. Consequently, individuals apply rules to protect themselves and maintain their privacy (Martin et al., 2017). By contrast, boundaries open up when individuals attribute altruistic motives to information requests. The response to the information request is not restricted but opens the gate for the flow of information between the parties.

Third, the results of Study 2 and 3 provide evidence that the communication content affects individuals' management of personal information. The results from Study 2 are in line with prior findings that found consumers respond more positively to self-benefit appeals (Holmes et al., 2002; Ryoo et al., 2020). This thesis has argued that an others-benefit message sent by a for-profit organization would be likely to amplify perceptions of opportunistic behaviors. The altruistic appeal might be counter-intuitive to the purpose of the organization and might raise concerns about persuasion attempts. These concerns shift the focus on egoistic motives, which increases the likelihood of flawed data. In extension of the prior research on persuasion, which highlights the positive effects of highly credible message endorsers in commercial settings only (Goldsmith et al., 2000; Reinhard & Messner, 2009; Rifon et al., 2004), the results from Study 3 provide a more nuanced view, considering both for-profit and not-for-profit organizations. A credible endorser can help not-for-profit organizations persuade individuals to open their information boundaries and reveal their health data truthfully. For-profit organizations that are supported by a less credible endorser, however, increase the likelihood that information gates are closed and that data are misrepresented.

This research also provides practical implications for healthcare organizations. In particular, for-profit organizations should frame persuasion messages for the request of personal data carefully to avoid negative reactions on individuals' intentions to disclose true information about them. They might work together with high-credibility endorsers, and they might focus on matched interests with providers of personal information (i.e., the benefit for the individual). Since experts with a medical background are perceived as being more credible than officials from government agencies when it comes to in providing health information (Avery, 2010), they might take into account domain-specific expertise.

Limitations and Future Research

Studies 1-3 are not without limitations. First, all three studies were done in the healthcare context with particular consideration of Covid-19. Since the epidemic has affected stakeholders of various kinds, this might have affected individuals’ intentions to disclose personal information depending on the requester. Future research might replicate the results for other diseases (e.g. cancer and rare diseases) or outside the context of healthcare.

Second, while the research focused on message framing and message endorser credibility, other factors such as two-sided communication (Fransen et al., 2015) might influence how and when individuals disclose personal information. Future research might find out whether two-sided messages are particularly helpful to for-profit organizations to increase the perception of altruism and decrease the perception of egoism to make individuals share true personal data with them.

Lastly, individuals’ attributions might go beyond the perception of altruistic versus egoistic motives. There is still no consensus on the classification of consumer attributions. Other studies have considered more than three dimensions (e.g. strategic-, stakeholder-, and value-driven), which might also be applicable to healthcare contexts (Ellen et al., 2006; Groza et al., 2011; Vlachos et al., 2009; Woisetschläger et al., 2017).

Conclusions from Studies 1-3

AI can help unlock the potential of big data for healthcare analytics. Yet, personal information about individuals is needed to get large datasets that feed AI tools. The bottleneck for the availability of these data to healthcare research often centers around individuals’ consent for their data to be used as well as the validity of the patient-reported data. The present research shows that individuals are more willing to disclose data if they perceive that the requesting organization is acting based on altruistic motives (i.e., the motives function as gate openers, as shown for university hospitals). Individuals are more likely to protect their data by intending to provide false information when they perceived egoistic motives to be the main driver for the organization requesting their data (i.e., the motives function as a privacy protection tool, as shown for pharmaceutical companies). The findings might be helpful to obtain valid and reliable data from individuals to support AI solutions in healthcare.

The next chapter addresses the second research question of this thesis and shifts the focus on consumers' contribution to the output component of Donabedian's quality assessment framework. It presents Study 4, which explores how the factors introduced in Chapter 3.3 (disease severity, social presence and innovativeness) impact consumers' responses to the integration of AI in the healthcare process.

5. Compliance with Medical Recommendations Depending on the Use of AI as a Diagnostic Method

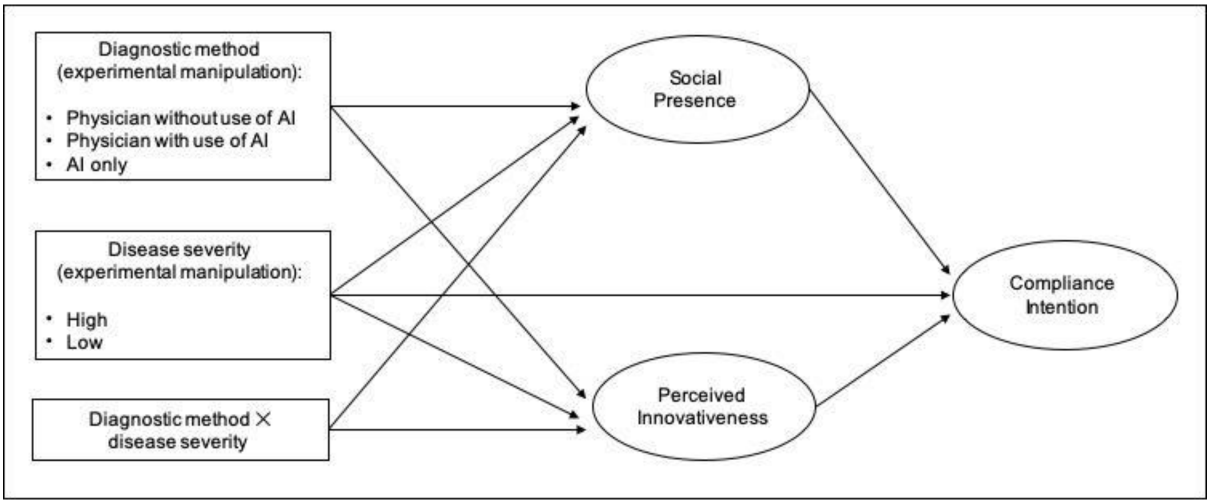
Many recent advancements in digitalization in healthcare build upon the use of big data. Digital technology-enabled big data analyses are considered to have the potential to disrupt the healthcare industry as a whole (Agarwal et al., 2010; Günther et al., 2017; Wang & Hajli, 2016). AI techniques are used in big data analyses to make predictions based on a set of rules. They run calculations from large datasets to estimate different possible solutions for a given problem, and thus enable data-driven decision-making (Pezzo & Pezzo, 2006). This is why AI might be particularly beneficial in healthcare to help prevent and treat diseases that (1) require learning from large populations; (2) follow patterns that can be detected by technology; and (3) are accessible to physicians and patients.

The advancements in information technology have changed the processes of how diagnoses and treatment recommendations are derived. Algorithms are trained to mimic physicians' decision-making rules by applying similar rationales when analyzing vast amounts of patient data. AI tools can diagnose certain diseases with expert-level accuracy, and even outperform human experts in some cases (Abramoff et al., 2018; Haenssle et al., 2018; Promberger & Baron, 2006). More specifically, AI can reduce human error, which is particularly beneficial in situations when a patient's safety is at risk (i.e., for highly [vs. less] severe diseases) (Balas, 2001). To help patients make the best decision in these situations, they aim to base their decision on experts with state-of-the-art scientific knowledge (which might be provided by AI) (Gino & Moore, 2007). Examples of recent uses of AI in this context include the detection of skin and breast cancer as well as of cardiac arrest (Abramoff et al., 2018).

5.1. Study 4 – Social Presence and Innovativeness

Addressing the second research question of this thesis, the aim of Study 4 was to explore whether the utilization of AI technologies in the medical assessment process influenced patient compliance with a recommended treatment. To better approach research question two, this study further specified three sub-research questions. First, it wanted to explore whether there were differences in an individual's intention to follow a medical recommendation depending on the diagnostic method used (physician, physician using AI, or automated AI tool alone) and the level of disease severity (high or low). Second, the study aimed to explore how individuals perceive the three diagnostic methods with regard to their social presence and innovativeness, as well as whether social presence and perceived innovativeness influence an individual's intention to comply with the treatment recommendation. Finally, the study aimed to explore whether social presence and perceived innovativeness mediate the relationship between the types of diagnostic methods and the individuals' intentions to follow the recommendation for the treatment of the disease. Figure 12 displays the conceptual model that guided this research.

Figure 12 *Conceptual Model (Study 4)*



5.2. Methods

Study Design and Sample

Study 4 used a 3 (diagnostic method: physician vs. physician who uses AI vs. automated AI tool) by 2 (severity of the disease: high vs. low) experimental design. Participants were randomly assigned to one of the six experimental conditions.

The study was conducted online, and participants were recruited through Amazon Mechanical Turk. The use of Amazon Mechanical Turk workers is appropriate given the design of the study (use of vignettes and a randomized assignment to experimental groups; see (Hopkin et al., 2019; Longoni et al., 2019) on the use of the population to study medicine- and health-related topics). The sample is limited to individuals who were 18 years of age or older and located in the US.

452 participants, 196 of them females (43.8%), participated in the study. All were located in the USA, with a mean age of 41.7 years (*SD* = 15.6) (see Table 13. The WHO reports that one in every three cancers diagnosed is a form of skin cancer, and according to statistics from the Skin Cancer Foundation, one in every five Americans will develop skin cancer in their lifetime ((World Health Organization, 2017). In our sample, 12.1% participants had previously been diagnosed with skin cancer, 28.8% of them had a previous skin cancer diagnosis in their family, while the remaining 59.2% did not have any skin cancer history.

Table 13 *Sample Characteristics (Study 4)*

Gender	Sample (%)	Age	Sample (%)	Education	Sample (%)	Skin cancer experience	Sample (%)
Female	43.8	18-25	6.0	High school	10.3	Yes	
Male	56.3	26-35	37.5	Some college	20.1	me	12.1
		36-45	13.9	Bachelor's degree	46.4	spouse/family	28.8
		46-55	12.0	Master's degree	21.2	No	59.2
		56-65	16.7	Professional degree	1.1		
		>65	13.9	Doctorate	.9		

Procedure and Decision Scenarios

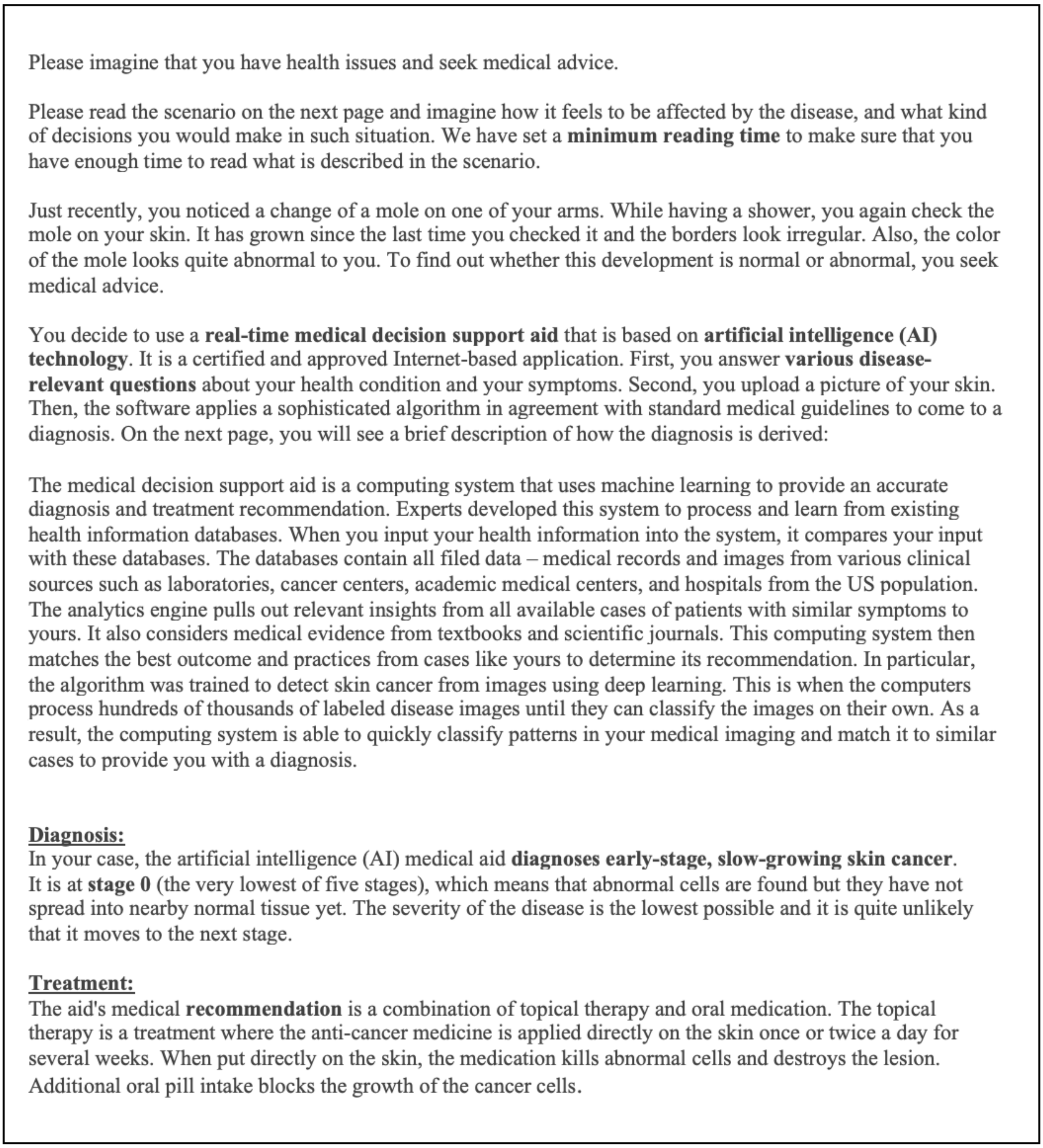
Prior to starting the study, informed consent was obtained and the study procedure was explained to the participants. During the study, the participants first read a hypothetical scenario and then filled in a survey. Participants were fully debriefed at the end of the study. The study meets the ethical principles for experimentation as stated in the Declaration of Helsinki.

Participants first read a scenario in which they were asked to imagine that they recently detected a change in their skin and are thus seeking medical advice. Six different versions of the scenario on the detection and treatment of skin cancer were developed, manipulating the diagnostic method and the severity of the disease. The scenario was kept similar in all other respects.

In the scenario, participants were asked to imagine that they recently noticed a change in a mole on their skin and that they decided to seek medical advice. The scenario then described a visit to a healthcare provider, where the medical assessment was performed either by a physician, a physician using AI technology, or an automated AI tool alone (described as a real-time medical-decision support aid based on AI technology). Further information was provided to the participants regarding how the respective method works to generate the diagnosis and treatment recommendation. Subsequently, half of the participants were told that the diagnosis of their disease (skin cancer) was not severe (stage 0) and the other half was told that it was severe (stage 2). Participants then read that they received a medical recommendation for the treatment, which was identical for each condition. After receiving the recommendation, participants indicated their intention to comply with it. Figure 13 shows one example of the vignettes that the participants read (for all vignettes see Appendix G).

Figure 13 *Manipulation of Diagnostic Method and Disease Severity (Study 4)*

Example vignette for the sole use of the automated AI tool as the diagnostic method (low severity)



Please imagine that you have health issues and seek medical advice.

Please read the scenario on the next page and imagine how it feels to be affected by the disease, and what kind of decisions you would make in such situation. We have set a **minimum reading time** to make sure that you have enough time to read what is described in the scenario.

Just recently, you noticed a change of a mole on one of your arms. While having a shower, you again check the mole on your skin. It has grown since the last time you checked it and the borders look irregular. Also, the color of the mole looks quite abnormal to you. To find out whether this development is normal or abnormal, you seek medical advice.

You decide to use a **real-time medical decision support aid** that is based on **artificial intelligence (AI) technology**. It is a certified and approved Internet-based application. First, you answer **various disease-relevant questions** about your health condition and your symptoms. Second, you upload a picture of your skin. Then, the software applies a sophisticated algorithm in agreement with standard medical guidelines to come to a diagnosis. On the next page, you will see a brief description of how the diagnosis is derived:

The medical decision support aid is a computing system that uses machine learning to provide an accurate diagnosis and treatment recommendation. Experts developed this system to process and learn from existing health information databases. When you input your health information into the system, it compares your input with these databases. The databases contain all filed data – medical records and images from various clinical sources such as laboratories, cancer centers, academic medical centers, and hospitals from the US population. The analytics engine pulls out relevant insights from all available cases of patients with similar symptoms to yours. It also considers medical evidence from textbooks and scientific journals. This computing system then matches the best outcome and practices from cases like yours to determine its recommendation. In particular, the algorithm was trained to detect skin cancer from images using deep learning. This is when the computers process hundreds of thousands of labeled disease images until they can classify the images on their own. As a result, the computing system is able to quickly classify patterns in your medical imaging and match it to similar cases to provide you with a diagnosis.

Diagnosis:
In your case, the artificial intelligence (AI) medical aid **diagnoses early-stage, slow-growing skin cancer**. It is at **stage 0** (the very lowest of five stages), which means that abnormal cells are found but they have not spread into nearby normal tissue yet. The severity of the disease is the lowest possible and it is quite unlikely that it moves to the next stage.

Treatment:
The aid's medical **recommendation** is a combination of topical therapy and oral medication. The topical therapy is a treatment where the anti-cancer medicine is applied directly on the skin once or twice a day for several weeks. When put directly on the skin, the medication kills abnormal cells and destroys the lesion. Additional oral pill intake blocks the growth of the cancer cells.

Measures

The intention to comply with the recommendation was measured via six items, rated on a seven-point rating scale (Appendix H). Amongst others, items included the following: “How likely would you follow the medical recommendation?”, anchored at 1 = very unlikely and 7 = very likely; “What is the probability that you will stick to the recommendation?”, anchored at 1 = very improbable and 7 = very probable. Internal consistency, as calculated by Cronbach’s alpha, was high (Cronbach’s alpha = .89).

Social presence measures were obtained from Gefen and Straub (2004) and adapted to the context of the study (Appendix I). The items included the following: “There is a sense of personalness in the process”; “There is a sense of sociability in the process”; and “There is a sense of human warmth in the process.” Participants rated their responses on a seven-point rating scale (1 = strongly disagree, 7 = strongly agree; Cronbach’s alpha = .96).

Perceived innovativeness of the diagnostic method was measured via three pre-tested items (Appendix I). Participants indicated their level of agreement to the following three statements: “There is a sense of technological advancement in the process”; “There is a sense of innovativeness in the process”; and “There is a sense of state-of-the-art knowledge generation in the process.” Participants rated their responses on a seven-point rating scale (1 = strongly disagree, 7 = strongly agree; Cronbach’s alpha = .84).

Analysis Plan

Analyses were conducted using SPSS 25. The study first examined descriptive statistics for the sample. Mean scores were computed for the latent variables. Then multiple linear regression analyses were conducted to test whether the two predictors (diagnostic method and disease severity) influenced the intention to comply with the medical recommendation, as well as social presence and innovativeness. For the analysis, two dummies were created as diagnostic method variables. The coding for the respective dummies was as follows: dummy one: physician = 1, other conditions = 0; dummy two: physician using AI = 1, other conditions = 0. The automated provider serves as a baseline for comparison in the analysis. Disease severity was coded as 0 = not severe and 1 = severe.

This study also examined whether social presence and innovativeness mediated the relationship between the diagnostic method and the intention to comply with the medical recommendation depending on the severity of the disease. This study used Hayes' PROCESS model 4 (version 3 for SPSS), including bootstrapping procedures. This is an approach that permits simultaneous testing of the direct, indirect and total effects of the type of diagnostic method, disease severity and interactions on the intention to follow the medical recommendation through the two parallel mediators. Two diagnostic method dummy variables (Spiller et al., 2013) were modeled as predictors; disease severity and the interactions of the two variables were included as covariates in the model. The dependent variable was the intention to comply with the recommendation.

5.3. Results

The model explains 23.4% of the variance in the intention to comply with the medical recommendation (see Figure 15 for the path coefficients). Figure 14 displays the mean scores of individuals' intention to comply with the medical recommendation for the two independent measures. It shows that overall compliance intentions were higher in case of a less severe disease compared to more severe disease. While in the low severity condition compliance intentions were higher for physicians as well as physicians supported by AI compared to the AI tool, in the high severity condition compliance intentions were comparable for all three diagnostic methods.

Figure 14 *Means and 95% Confidence Intervals for Compliance Intentions in High and Low Severity for the Three Diagnostic Methods (Study 4)*

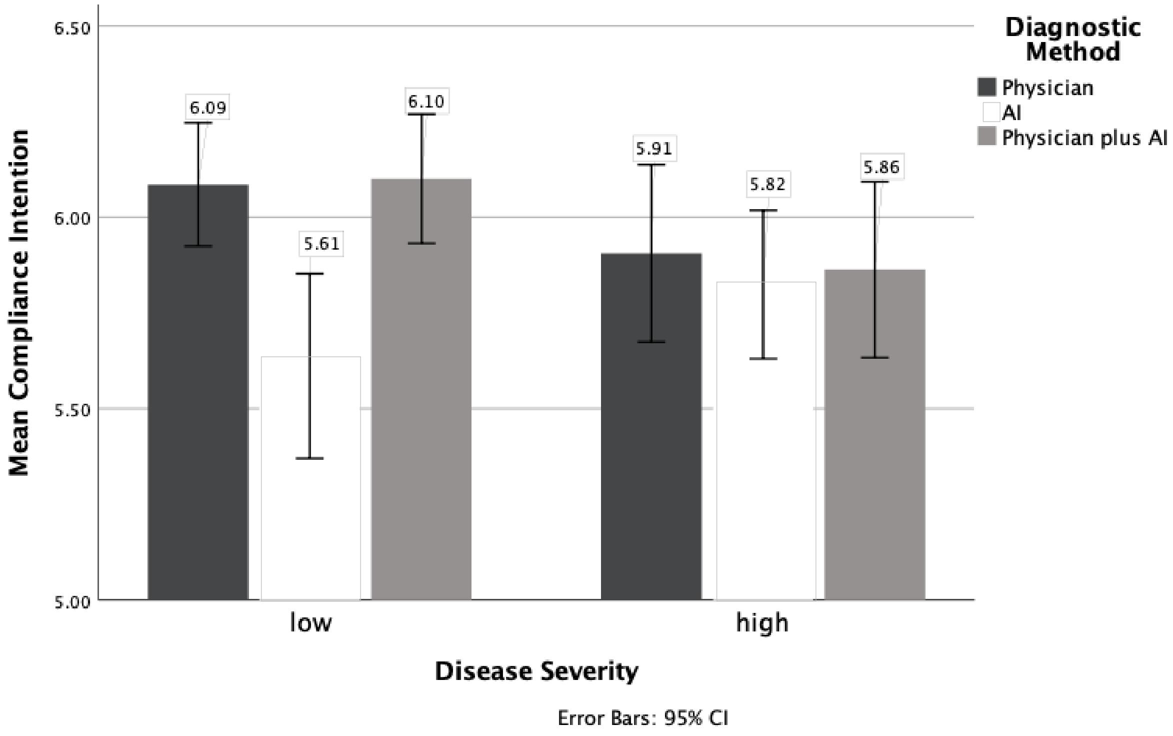


Table 14 summarizes the results of the mediation analysis. Compared to the automated AI tool alone, the intention to comply with the medical recommendation was significantly greater for the physician (*ß* = .40, *SE*= .14, *p* = .005) and physician using AI (*ß* = .27, *SE* =.14, *p* = .05) variables. The difference between the physician using AI and the physician variable was non-significant (*ß* = –.14, *SE* = .13, *p* = .30).The effect of the severity of the disease on the intention to comply with the medical recommendation was non-significant (*ß* = .15, *SE* = .13, *p* = .24). The analysis revealed one significant interaction effect between the physician using AI (vs. the automated AI tool alone) and the severity of the disease (*ß* = –.40, *SE* = .19, *p* = .03). The participants' intention to follow the medical recommendation was greater in the scenario of the physician using AI compared to the automated AI tool when the severity of the disease was low (but not when it was high).

The effects of both social presence (*ß* = .11, *SE* = .28, *p* < .001) and perceived innovativeness (*ß* = .37, *SE* = .04, *p* < .001) on the intention to comply with the medical recommendation were significant. Furthermore, social presence was higher when a physician (*ß* = 1.95, *SE* = .23, *p* < .001) or a physician using AI (*ß* = 1.76, *SE* = .23, *p* < .001) made the assessment, compared to the automated AI tool alone. The effect on social presence was not significantly different between the physician and the physician using AI.

Perceived innovativeness was higher when a physician using AI (ß = .46, SE = .15, p = .002) or when the automated AI tool (*ß* = –.41, *SE* = .15, *p* = .01) made the assessment, compared to the physician not using AI. The effect on perceived innovativeness was not significantly different for the comparison between the automated AI tool and the physician using AI.

The severity of the disease had no significant effect on social presence (*ß* = .21, *SE* = .23, *p* = .35) or perceived innovativeness (*ß* = .07, *SE* = .15, *p* = .66). All interaction effects between the diagnostic method and the disease severity on the two mediators were non-significant.

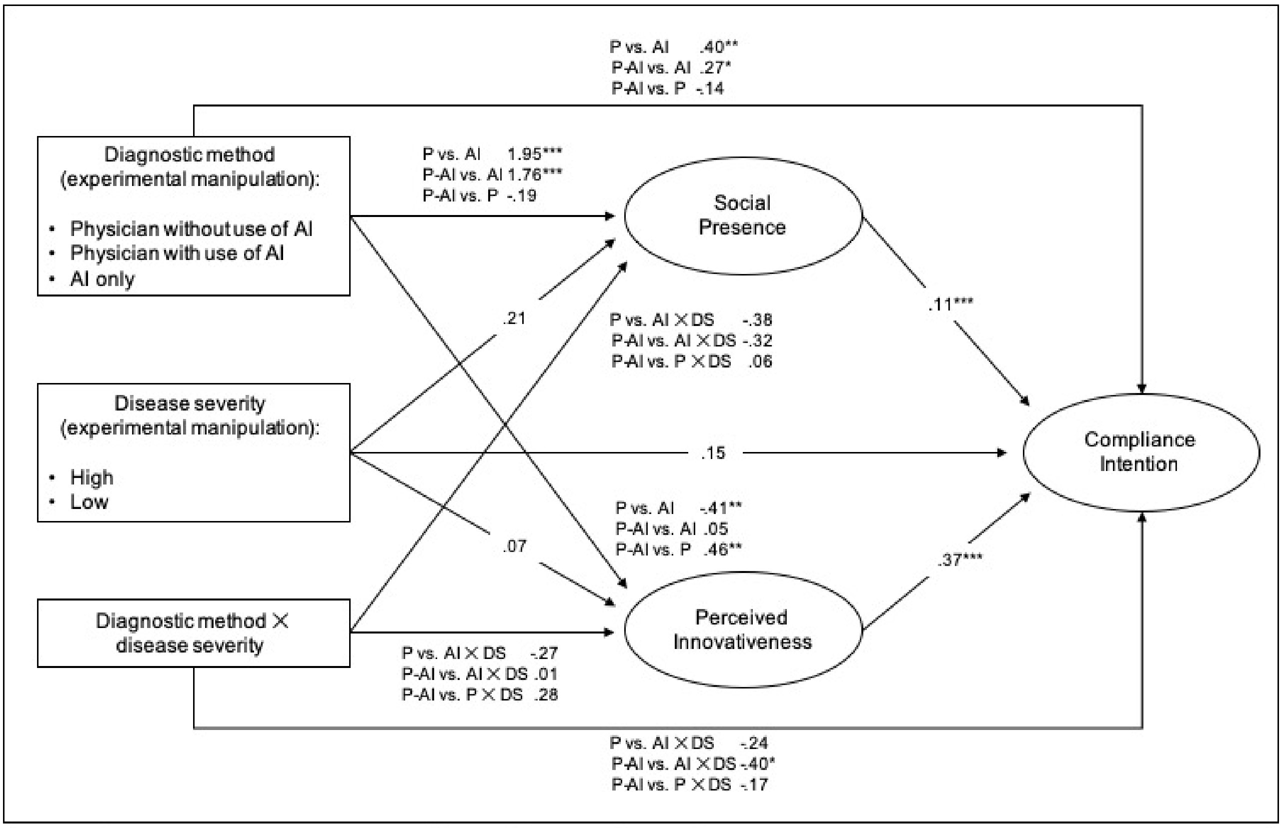
Next, the indirect effects of the type of diagnostic method on an individual's intention to comply with the medical recommendation were calculated. For the comparison between the physician and the automated AI tool, both social presence (*ß* = .22, 95% confidence interval (*CI*) [.09, .39]) and perceived innovativeness (*ß* = –.15, *95% CI* [–.28, –.04]) were significant mediators (the CI excludes zero). For the comparison between the physician using AI and the automated AI tool, social presence (*ß* = .20, *95% CI* [.07, .36]), but not perceived innovativeness (*ß* = .02, *95% CI* [–.09, .12]), was a significant mediator. When comparing the physician using AI with the physician alone, there was a significant indirect effect via perceived innovativeness (*ß* = .17, *95% CI* [.06, .30]) but not via social presence (*ß* = –.02, *95% CI* [–.01, .07]).

Table 14 *Results of Mediation Effect of Social Presence and Innovativeness (Study 4)*

Direct effects on the mediators	***B***	**SE**	***p***
Constant	3.66	.16	< .001
Physician → social presence	1.95	.23	< .001
Physician plus AI → social presence	1.76	.23	< .001
Disease severity → social presence	.21	.23	.35
Physician × disease severity → social presence	–.32	.32	.32
Physician plus AI × disease severity → social presence	–.38	.32	.24
Constant	5.98	.11	< .001
Physician → perceived innovativeness	–.41	.15	.002
Physician plus AI → perceived innovativeness	.05	.15	.73
Disease severity → perceived innovativeness	.07	.15	.66
Physician × disease severity → perceived innovativeness	–.27	.21	.20
Physician plus AI × disease severity → perceived innovativeness	.01	.21	.98
Direct effects on the dependent variable	***B***	**SE**	***p***
Constant	2.96	.27	< .001
Physician → compliance intention	.40	.14	.005
Physician plus AI → compliance intention	.27	.14	.05
Social presence → compliance intention	.11	.03	< .001
Perceived innovativeness → compliance intention	.37	.04	< .001
Disease severity → compliance intention	.15	.13	.24
Physician × disease severity → compliance intention	–.24	.19	.20
Physician plus AI × disease severity → compliance intention	–.40	.19	.03
Indirect effects via the mediators	***B***		**[95% CI]**
Physician, total indirect effect	.07		[–.12, .29]
Via social presence	.22		[.09, .39]
Via perceived innovativeness	–.15		[–.28, –.04]
Physician plus AI, total indirect	.22		[.03, .41]
Via social presence	.20		[.07, .36]
Via perceived innovativeness	.02		[–.09, .12]

Notes: The experimental group that was assigned to the automated AI tool as the diagnostic method served as the reference group for comparison with dummy one (physician) and dummy two (physician plus AI). *B* = Unstandardized path coefficient, *SE* = Standard error, *p* = Significance, *CI* = Confidence interval.

Figure 15 *Results of the Mediation Model (Study 4)*



Note: The figure displays unstandardized beta coefficients; *** *P* < .001, ** *P* < .01, * *P* < .05
Abbreviations: P = physician without use of AI; P-AI = physician with use of AI; AI = AI only; DS = disease severity

5.4. Discussion of the Results of Study 4

The study tested three different levels of AI integration in the diagnostic method: a) no integration (medical assessment was provided only by a physician), b) hybrid integration (medical assessment of a physician was supported by an AI tool), c) full integration (the medical assessment of a physician was fully replaced by an automated AI tool). The purpose of the study was to explore whether the utilization of AI technology in the medical assessment process as well as the severity of a diagnosed disease influenced patients' compliance intentions with the recommended treatment. The results of the experimental study, which used skin cancer as the case, showed that intention to follow the medical recommendation was greater for the physician compared to the automated AI tool alone (regardless of disease severity) and for the physician using AI compared to the automated AI tool alone (in the case of low disease severity). There was no difference between the physician using AI and the physician alone. The results thus indicate that individuals were most likely to stick to the recommendations, a factor that should increase recovery and health outcomes (Bonaccio & Dalal, 2006), when human expertise was central to the diagnosis and the treatment recommendation (vs. an automated AI tool).

Intention to follow the medical recommendation was greater in the case of the physician using AI as compared to the automated AI tool alone when the severity of the disease was low (but not when it was high). Thus, when AI was included in a physician's efforts, the treatment recommendations for less severe diseases were more likely to be accepted as compared to recommendations made by an automated AI tool alone (which most of the individuals resisted adhering to). When only humans were involved in the medical assessment, social presence was high and the innovativeness perception was low (vs. use of an automated AI tool), which influenced intended compliance. When only AI is used for an automated assessment, innovativeness perception was high but social presence was low (vs. when a physician was involved), which also influenced intended compliance. There was no significant difference between the physician using AI and the automated AI tool alone in terms of perceived innovativeness, and it did not impair social presence.

Limitations and Future Research

Study 4 has several limitations. First, participants were not able to choose their preferred diagnostic method. They were randomly assigned to one of the three methods. A lack of trust in the method could have had a negative effect on individuals' compliance intentions. Also, there might be differences in the degree of familiarity with the various diagnostic methods based on previous personal experiences. While individuals might be more familiar with the medical service provided by a physician, they might be less familiar with the use of AI in healthcare. Although it is impossible to rule out the influence of these past learnings in empirical studies, future research could assess the influence of trust and habits on the acceptance of and compliance with AI-derived or AI-supported medical decisions.

Second, instead of manipulating the severity of the disease, future research might manipulate the complexity of the disease (given AI's ability to solve complex problems). If patients are informed about the high (vs. low) complexity of diseases, they might be more open towards AI-derived or AI-supported medical decisions. In the present study, the type of disease was kept constant to rule out alternative explanations (implying that similar processes produce skin cancer cells). Future research might use different diseases to manipulate the complexity or use vignettes with different descriptions of the complexity of a disease. Furthermore, the manipulation of disease severity is somewhat confounded with the manipulation of the diagnostic method. Because the patient received the information about the severity level from the provider, the effectiveness of the manipulation might depend on the degree to which the person actually believes the provider (see our remarks on trust and familiarity above).

Third, it was not real patients but only behavioral intentions that were assessed in the studies. Future studies might consider patients who have been diagnosed with the disease and who are willing to report their actual compliance-related behavior (e.g., intake of medicine, behavioral changes). Also, in the present study, the scenarios did not mention any particular aspects of human warmth (e.g., conversations, empathy from physicians), thereby restraining the context for social presence. Future studies might also focus on the reciprocal interaction between patients and healthcare service providers. This might increase the external validity of the findings.

Implications for Practice

Study 4 makes three important contributions to the medical decision-making literature. First, it extends social presence theory by proposing two pathways for an individual's compliance with treatment recommendations via social presence and perceived innovativeness. Previous studies have looked at social presence as the sole mediator, even though researchers have criticized how the concept falls short with regard to the technology-enabling characteristics of the interaction, such as an agent's capability to be up-to-date, innovative and act according to the state-of-the-art of knowledge (Lu et al., 2016). The present study partially fills this research void.

Second, the study shows that the pathways have different magnitudes depending on the diagnostic method under consideration (physician vs. physician using AI vs. automated AI tool alone). The involvement of humans and the involvement of technology in the medical assessment may operate via different mechanisms when individuals form compliance intentions. These findings are of interest to compliance research, indicating that AI tools may need a high degree of innovativeness in order to increase compliance intentions (Pezzo & Pezzo, 2006).

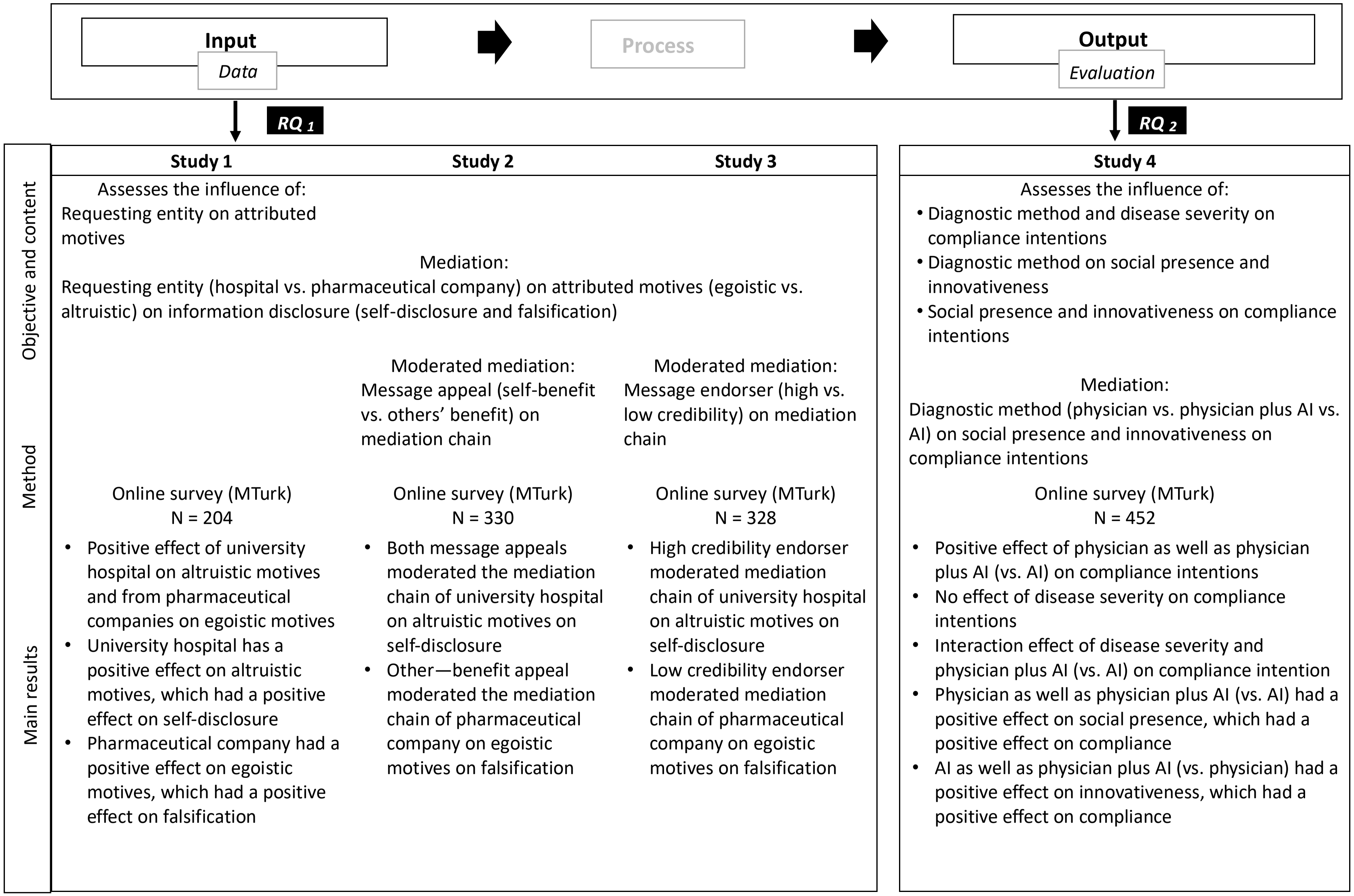
Third, contrary to our assumption participants' adherence intentions were higher when diagnosed with a disease relatively low in seriousness, by a physician using AI, compared to a more serious condition. This is in line with previous findings that those who are worse in health are less likely to be adherent (Christensen et al., 2009; DiMatteo et al., 2007). A potential explanation is that many physical, psychological and practical limitations disrupt patients' adherence efforts (DiMatteo et al., 2007). Patients may have doubts about the efficacy of their treatments , their expectations for and interactions with their provider may be reduced in quality as they grow more severely ill, or they may become hopeless or depressed (Kravitz et al., 2002). Another explanation could be that patients in a less severe condition are more likely to adhere to the recommendation because they fear that their condition could otherwise deteriorate. Our findings highlight that it should be recognized that patients facing serious illness are at great risk of nonadherence. Thus, to help them to effectively cope with the complexities of the illness and foster adherence, it is important to pay attention to patients' awareness and understanding of the severity.

Finally, the study provides evidence for the general notion that a human–technology combination (here, physicians' use of AI to diagnose a disease) may lead to compliance intentions that are as high as with physician-only consults. Most importantly, for the case of skin cancer considered here, the sole use of AI technology as a diagnostic method might negatively affect the intent to comply with the recommendation treating the disease. In contrast to previous findings (Arkes et al., 2007), our results have positive implications for healthcare service providers considering the implementation of AI tools. The sole use of AI as a diagnostic method cannot be recommended based on the results of the present study. Still, as a means to promote the perception of innovativeness, physicians might use AI tools as a diagnostic aid. Physicians therefore have the option to integrate and utilize suitable hardware and software that combine the expertise of technology with the physician's expertise.

6. General Conclusion

The purpose of this thesis was to investigate consumers' role in the value creation of AI health applications. Taking the perspective of Donabedian's (1983) quality assessment framework on AI value creation process, this thesis focused on the two components where the involvement of consumers is most needed to achieve high quality AI solutions: AI input and output. Two research questions, each focusing on one aspect of consumers' contribution to AI value creation, guided this research of four empirical studies. Figure 16 provides an overview of the main objectives of the studies and summarizes their major findings.

Figure 16 *Summary of Results Studies 1 to 4*



	Study 1	Study 2	Study 3	Study 4
Objective and content	Assesses the influence of: Requesting entity on attributed motives			Assesses the influence of: • Diagnostic method and disease severity on compliance intentions • Diagnostic method on social presence and innovativeness • Social presence and innovativeness on compliance intentions
	Mediation: Requesting entity (hospital vs. pharmaceutical company) on attributed motives (egoistic vs. altruistic) on information disclosure (self-disclosure and falsification)			
		Moderated mediation: Message appeal (self-benefit vs. others' benefit) on mediation chain	Moderated mediation: Message endorser (high vs. low credibility) on mediation chain	Mediation: Diagnostic method (physician vs. physician plus AI vs. AI) on social presence and innovativeness on compliance intentions
Method	Online survey (MTurk) N = 204	Online survey (MTurk) N = 330	Online survey (MTurk) N = 328	Online survey (MTurk) N = 452
Main results	• Positive effect of university hospital on altruistic motives and from pharmaceutical companies on egoistic motives • University hospital has a positive effect on altruistic motives, which had a positive effect on self-disclosure • Pharmaceutical company had a positive effect on egoistic motives, which had a positive effect on falsification	• Both message appeals moderated the mediation chain of university hospital on altruistic motives on self-disclosure • Other—benefit appeal moderated the mediation chain of pharmaceutical company on egoistic motives on falsification	• High credibility endorser moderated mediation chain of university hospital on altruistic motives on self-disclosure • Low credibility endorser moderated mediation chain of pharmaceutical company on egoistic motives on falsification	• Positive effect of physician as well as physician plus AI (vs. AI) on compliance intentions • No effect of disease severity on compliance intentions • Interaction effect of disease severity and physician plus AI (vs. AI) on compliance intention • Physician as well as physician plus AI (vs. AI) had a positive effect on social presence, which had a positive effect on compliance • AI as well as physician plus AI (vs. physician) had a positive effect on innovativeness, which had a positive effect on compliance

Research question one was related to consumers' involvement in the creation of valuable data, which are the most important input factor for AI solutions. The potential of AI to create high-quality health service applications highly depends on the quantity and quality of its input. Health data are a critical resource for AI value creation. Research on individuals' information-sharing behavior found that personal health information is highly sensitive data that people are rather reluctant to share (Bansal et al., 2010; Mothersbaugh et al., 2012). Individuals' decisions to allow or restrict access to their personal health information is influenced by several contextual and risk factors (Petronio, 2002). Among those is the entity requesting the information (Anderson & Agarwal, 2011) whose impact on individuals' information sharing is demonstrated with three empirical studies. Moreover, this thesis introduced individuals' attributed motives to healthcare organizations' information requests as a novel factor that helps to gain more insights into individuals' information management. Since the quality of an AI application is not only determined by the quantity of data that it is based on but also on the quality of the data, the studies incorporated two dimensions of information sharing: self-disclosure and falsification intention. Prior research largely considered these constructs separately (Martin et al., 2017; Mothersbaugh et al., 2012). For the future development of AI in healthcare, both factors are crucial for quality considerations of AI solutions. The findings suggest that measures must be implemented already in the first stage of AI value creation to counteract adverse downstream effects on AI health solutions. Biases from false information must be considered in the development of AI applications to avoid harm to individuals' health. Besides the implementation of appropriate measures in response to low-quality data, it is important to establish an environment that facilitates open information sharing for consumers. One way for healthcare organizations is to be transparent about the collection and handling of personal information. On top of that, tools need to be introduced that give consumers more oversight and control over their collected data. In this way, patients can take responsibility of their data and at the same time encourages them to get more involved and to actively shape healthcare solutions towards their own needs.

Research question two was related to consumers' involvement in the assessment of the output of AI value creation. This thesis investigated the evaluation of AI output in the form of individuals' compliance with a medical recommendation generated with different levels of AI involvement. Past research found that individuals are rather reluctant to accept algorithmic advice (Castelo et al., 2019; Dietvorst et al., 2015), especially in the medical context (Longoni et al., 2019). In line with this research the results of Study 4 showed that individuals choose the medical recommendation of a physician, or a physician supported by AI, over the one of an algorithmic tool. However, in contrast to previous research (Arkes et al., 2007; Pezzo & Pezzo, 2006), this thesis provided empirical evidence that the combination of human and algorithmic expertise in the medical process does not have adverse effects on individuals' compliance. Furthermore, two factors of the medical process – social presence and innovativeness – helped explain individuals' compliance intentions. Overall, the results show that the integration of AI in the medical process is conditionally valued by patients. These findings suggest two major prospects for the future development of AI applications in healthcare. First, it highlights that the state-of-the-art knowledge AI integrates into the medical process creates added value to patients. This capability could be further advanced and exploited e.g. in the form of healthcare applications, such as personalized medication or treatments, that are tailored to address individual needs and preferences. However, to evolve its positive impact on individuals' compliance intentions, and thus ultimately to better health outcomes, a combination with a human expert seems necessary. Second, AI alone still lacks important socio-emotional and relational elements that are crucial to increase patients' compliance and satisfaction (Barbosa et al., 2012; Kardas et al., 2013). Even though there are attempts to increase AI's humanness (Heerink et al., 2010) it is still questionable if it will be able to convey the emotional support humans need for their health decision-making. Again, the combination of human and algorithmic expertise poses the most promising way for a successful implementation of AI in healthcare. AI should be developed to complement human skills so that the emerging synergies improve the quality of care according to patients' needs.

6.1. Theoretical and Practical Implications

Several theoretical and practical implications can be deduced from the findings presented in this thesis. First, it contributes to information systems literature by providing evidence that information disclosure is a multifaceted construct. To fully capture individuals' information management measuring only individuals' self-disclosure or non-disclosure (Anderson & Agarwal, 2011; Bansal et al., 2010; Lin et al., 2016; Zhang et al., 2018) is insufficient. While disclosure provides a good indication about the amount of information individuals intend to share, it neglects the aspect of accuracy. The veracity of health data is a critical aspect for AI health applications, where consequences of inaccurate data can have detrimental effects on peoples' health and safety. To address this gap this thesis applied a dual approach by incorporating individuals' intentions to falsify information. Thus, this research advances the understanding of how individuals manage information sharing.

Second, this thesis introduces individuals' motive attributions to the information management context. Prior research on motive attributions was mainly conducted in marketing contexts, including cause-related marketing (Barone et al., 2007), corporate social responsibility (Groza et al., 2011) or sponsorship (Woisetschläger et al., 2017). This research shows that attributed motives (altruistic and egoistic) are highly relevant in the information-sharing context. While perceived egoistic motives elicit information protection intentions, altruistic motives function as gate openers and enable the flow of true information exchange.

Third, two studies (Study 2 and 3) provide evidence that organizations' communication activities are additional contextual factors that affect individuals' information management. This thesis investigated the moderating impact of two message-related factors (message appeal and message endorsers' credibility) on individuals' disclosure intentions. Findings showed that message appeal can amplify individuals' motive perceptions of the information-requesting healthcare organization. In the case of a for-profit organization, this thesis revealed that the altruistic appeal of an others-benefit message appeal might be perceived by consumers as conflicting with the for-profit orientation of the organization and thus raise concerns of persuasion attempts by the organization which increase attributions of egoistic motives. Attributed egoistic motives in turn increase the misrepresentation of information as a defensive mechanism. On the other hand, Study 3 showed that a less credible message sources can be detrimental for for-profit organizations since they prompt individuals to be even more protective about their personal information. In contrast to that, a credible endorser can help not-for-profit organizations to persuade individuals to open their boundaries and share true information.

Fourth, findings contribute to medical decision-making literature. Study 4 extends social presence theory by proposing a second pathway for individuals' compliance via perceived innovativeness. This shows that compliance is affected by socio-emotional (social presence) as well as functional (innovativeness) aspects of the medical process. Additionally, these two factors also help to explain the differences in individuals' compliance intentions depending on who performs the medical assessment. When AI is involved in the diagnostic method, functional aspects are more likely to increase compliance intentions.

This thesis also provides practical implications for healthcare organizations. The results from Studies 1-3 in particular may be highly relevant to for-profit healthcare organizations. For-profit organizations need to be aware that their information requests, even if they are not for commercial purposes, might be perceived as egoistically motivated. To mitigate the negative effects on data collection, they may use persuasive communications tools. However, as the results of this research suggest, organizations need to be cautious about the right framing of the message and only select a message endorser with high credibility to promote their attempts.

Finally, the findings of Study 4 suggest that the incorporation of AI tools in the medical assessment can be highly valuable. In contrast to previous findings (Arkes et al., 2007), individuals indicated similar compliance indentations to recommendations by a physician independent of their utilization of AI. Consumers value the aspect of innovativeness in healthcare delivery, which should foster implementation of AI tools in support of human expertise.

6.2. Limitations and Future Research

The studies of this thesis are not without limitations, which grants an opportunity for future research. First, all studies used self-reported measurement constructs and did not address real patients. Using self-reported measurements entails the possibility of certain biases, such as social desirability bias. Therefore, one suggestion for future research would be to incorporate behavioral measures to assess actual behavior with regards to information disclosure or acceptance of AI health applications. Furthermore, future research might consider real patients who have been diagnosed with a certain disease and assess their actual compliance behavior (e.g. intake of medicine, behavior change) to provide more real-world evidence about the effectiveness in clinical practice.

Second, Studies 1-3 were conducted during the outbreak of the COVID-19 pandemic. The consideration of COVID-19 in the studies might have affected individuals' intentions to disclose personal information for research purposes. It could also have affected the perceptions of the different stakeholders asking for information. In light of the increasing need for vaccine development, individuals might have evaluated requests from pharmaceutical companies more favorably. Future research might replicate the results for other diseases (e.g. cancer, rare diseases) or other contexts outside healthcare.

Third, motive perceptions that individuals attribute to health organizations' requests might be more multifaceted. Future research could investigate if there are other attribution dimensions besides altruism and egoism that impact information sharing. For example, individuals might assume that healthcare organizations are doing their "civic duty" and are acting on external expectations, which might cause associations of responsibility and accountability resulting in positive responses to information sharing requests.

Fourth, in Study 4, participants could not choose their preferred diagnostic method but were randomly assigned to one of the three methods. Compliance intentions could be negatively affected by a lack of trust or familiarity with the different methods. Given that AI is a relatively new method in the healthcare setting, it is very likely that individuals are less familiar with its use in healthcare services. Future research could assess the influence of trust, familiarity, risk perception, habits or attitudes on the acceptance of and compliance with AI health services.

Finally, the scenario in Study 4 did not particularly mention aspects of human warmth (e.g. empathy, caring in conversation), thereby restraining the context for social presence. Future studies might manipulate the level of social presence or other relational and socio-emotional aspects in health service delivery.

AI applications are emerging in many healthcare domains, from disease detection to medical decision-making. The impact of AI applications on the healthcare landscape highly depends on its ability to co-evolve with its users. The findings of this thesis underline that incorporating consumers' preferences and perspectives is important for the development of high-quality AI applications for healthcare. Consumers not only indirectly shape AI value creation by accepting or adopting its output (e.g. treatment recommendation), but they also directly determine the quality of the results by sharing accurate health data that feed AI value creation in the first place. At least in the near future the role of AI in healthcare will not be in the form of a super-intelligent machine that replaces human workers in all aspects. However, this thesis has shown that human and AI collaboration can be a key contributor to value creation in health services – and it may prove to be an important stepping stone for the increasing implementation of AI in healthcare.

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Appendix

Appendix A *Hypothetical Scenario Provided to the Participants (Studies 1-3)*

First, please read the hypothetical scenario on the next page carefully and picture yourself in the specified circumstances.

Given the current situation with the COVID-19 virus the [university hospital “MWC General Hospital”/ pharmaceutical company “MWC Pharma”] announced that they are setting up a comprehensive database of people’s health data to make better predictions about the virus, to improve current and future management of the virus, and to support people with recommendations on how to cope with their daily health challenges.

[“MWC General Hospital”/“MWC Pharma”] is known to be committed to leading the revolution in healthcare through cutting edge technology. It aims to expand medical knowledge and advance health and well-being.

To address the evolving needs of patients they make use of their superior competences in artificial intelligence across various areas. To meet their goals and to ensure that the outcomes are as precise as possible, “MWC General Hospital” [“MWC General Hospital”/“MWC Pharma”] requires a large amount of health data. On this basis they call upon the general population to contribute to this database

To do that, you access the secure website of [“MWC General Hospital”/“MWC Pharma”]. Here, you will be asked about which kind of personal data you would be willing to provide. The data does not only refer to virus-related health patterns but focuses on predictors of peoples’ likelihood to be infected, to recover and to be treated accordingly.

Notes: Terms in brackets [ ] are the two variants of the manipulation of the requesting entity that were randomly assigned to the participants. Depending on the experimental condition participants either read one or the other of the variant descriptions.

Appendix B *Variables for Management of Personal Information (Studies 1-3)*

Items	Study 1				Study 2				Study 3			
	PC		UH		PC		UH		PC		UH	
Self-Disclosure Please specify the extent to which you would be willing to reveal the following personal information	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
Demographics e.g. age, gender	5.60	1.48	5.96	1.32	5.31	1.70	5.87	1.20	5.38	1.72	5.71	1.52
Current health condition e.g. symptoms, illnesses, chronic disease, hospitalization	5.46	1.63	5.77	1.28	4.85	1.91	5.48	1.45	4.88	2.00	5.27	1.63
General health e.g. smoking habits, BMI, physical activity, diet, weight, sleeping habits, alcohol consumption	5.39	1.52	5.76	1.35	4.83	1.85	5.51	1.58	4.91	1.93	5.26	1.66
Surgery e.g. transplants, plastic surgery, hip replacement	5.09	1.69	5.70	1.30	4.59	1.98	5.30	1.79	4.79	1.90	5.17	1.75
Medication e.g. prescribed mediation, over the counter medication, medication adherence	5.11	1.70	5.66	1.30	4.67	2.03	5.35	1.61	4.80	1.95	5.01	1.75
Occupation	5.11	1.83	5.64	1.41	5.06	1.84	5.46	1.61	4.88	1.95	5.17	1.76
Lifestyle e.g. amount of leisure time, working hours, mobility/transportation behavior	5.03	1.65	5.49	1.38	4.84	1.91	5.31	1.66	4.79	1.91	4.98	1.75
Medical history e.g. previous illnesses, injuries, surgeries	4.96	1.63	5.51	1.44	4.52	2.04	5.44	1.52	4.77	1.96	5.07	1.76
Test results e.g. blood pressure, cholesterol level, screening results, mammogram results	4.92	1.86	5.46	1.44	4.61	2.01	5.35	1.60	4.76	1.87	5.07	1.72
Substance abuse e.g. drug, medication or alcohol abuse	4.94	1.84	5.42	1.42	4.31	1.98	5.04	1.87	4.46	2.11	4.59	1.96
Emotional information e.g. happiness, sadness, fear	4.92	1.78	5.20	1.56	4.53	1.89	5.11	1.76	4.62	2.11	4.71	1.87
Sexual health information e.g. sexual transmitted diseases, HIV	4.79	1.84	5.26	1.65	4.40	2.09	5.01	1.92	4.50	2.15	4.72	1.94
Mental health information e.g. psychological therapy or counseling, depression, anxiety disorder, suicide attempts, eating disorder	4.97	1.79	5.00	1.84	4.12	1.99	5.01	1.84	4.46	2.12	4.67	1.98
Reproductive information e.g. fertility information, miscarriage, abortion	4.42	2.01	4.93	1.76	4.20	2.14	4.93	1.91	4.40	2.07	4.62	1.96
Genetic information e.g. genetic test information, paternity test	4.41	2.09	4.94	1.92	4.25	2.09	4.78	1.96	4.41	2.12	4.46	2.08
Social activity & media usage e.g. frequency social contacts, amount of media usage	4.57	1.88	4.70	1.90	4.26	2.08	4.71	1.99	4.24	2.15	4.28	2.06
Contact information e.g. address, phone number, ZIP code	4.29	1.96	4.94	1.80	4.06	2.22	4.81	1.90	4.35	2.03	4.52	1.96
Shopping habits e.g. frequency, location, time	4.43	2.00	4.68	1.78	4.37	2.08	4.72	2.01	4.37	2.06	4.30	1.96

Sensory data e.g. mobile device, wearables	4.19	1.92	4.65	1.86	4.05	2.13	4.67	2.00	3.98	2.07	4.25	2.11
Location data e.g. GPS, Bluetooth	3.99	2.08	4.14	2.12	3.85	2.13	4.17	2.06	3.74	2.12	3.71	2.11
Falsification intentions	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
I am likely to give false information	3.16	2.04	2.95	2.15	2.97	1.95	3.03	2.09	3.04	2.03	3.06	2.06
I purposely try to trick when providing my personal data	3.07	1.98	3.03	1.99	2.97	1.93	3.07	2.01	3.05	2.00	3.18	2.13
I think it is fine to give misleading answers on personal questions	3.08	2.02	3.12	2.15	2.98	1.88	3.25	2.18	3.12	2.05	3.20	2.09
I would only fill up data partially	4.09	2.05	3.94	2.00	4.06	1.91	3.87	1.98	4.02	2.00	4.30	1.95

Notes: M = Mean; SD = Standard deviation; PC = Pharmaceutical company; UH = University hospital. For self-disclosure intentions items, individuals indicated their willingness to reveal personal information of the different categories on a seven-point scale, with response options ranging from 1 = very unlikely to 7= very likely. For falsification items, individuals indicated their willingness to falsify personal information on a seven-point scale, with response options ranging from 1 = very unlikely to 7= very likely.

Appendix C *Variables for Motive Perception (Studies 1-3)*

Items	**Study 1**				**Study 2**				**Study 3**			
	PC		**UH**		**PC**		**UH**		**PC**		**UH**	
When you think about potential reasons why “MWC General Hospital” is collecting your personal data to set up this database, how much do you agree with the following explanations? The university hospital is collecting my persona data to set up a database because they…												
Altruistic motives	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
…ultimately care about people	4.90	1.57	5.32	1.28	4.54	1.53	5.39	1.12	4.66	1.59	5.04	1.49
…have a genuine concern for the welfare of people	4.93	1.50	5.43	1.19	4.74	1.53	5.45	1.09	4.74	1.68	5.21	1.38
…really care about getting health information to people	4.99	1.42	5.38	1.31	4.84	1.58	5.34	1.10	4.82	1.66	5.21	1.36
…want to help people to help	5.06	1.39	5.36	1.31	4.86	1.47	5.38	1.14	4.82	1.56	5.24	1.31
…believe it is morally the “right” thing to do	4.86	1.46	5.05	1.44	4.64	1.57	5.32	1.30	4.65	1.66	4.91	1.52
…have a long-terms interest in the community	4.98	1.44	5.30	1.30	4.86	1.53	5.35	1.17	4.71	1.61	5.10	1.45
…are trying to give back something to the community	4.82	1.63	5.16	1.30	4.59	1.62	5.14	1.27	4.66	1.66	4.95	1.57
…want to make it easier for people who care about the cause to support it	5.18	1.30	5.24	1.19	4.82	1.44	5.31	1.23	4.87	1.56	4.89	1.54
Egoistic motives	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
…want to get publicity	4.73	1.59	4.41	1.56	4.83	1.49	4.52	1.71	4.96	1.45	4.35	1.74
…are taking advantage of the cause to help their own business	4.74	1.68	4.34	1.71	4.84	1.59	4.33	1.80	4.82	1.58	4.44	1.77
…want to help themselves	5.16	1.33	4.84	1.44	5.22	1.38	4.61	1.60	5.12	1.48	4.68	1.64
…will keep more customers by making this offer	4.81	1.49	4.41	1.54	4.78	1.47	4.71	1.58	4.72	1.37	4.66	1.74
…will get more customers by making this offer	4.82	1.55	4.43	1.56	4.99	1.42	4.56	1.65	4.84	1.45	4.49	1.71
…hope to increase profits by making this offer	5.02	1.50	4.54	1.64	5.11	1.47	4.74	1.69	5.24	1.43	4.56	1.75
…believe it creates a positive corporate image	4.73	1.59	4.41	1.56	4.83	1.49	4.52	1.71	4.96	1.45	4.35	1.74

Notes: M = Mean; SD = Standard deviation; PC = Pharmaceutical company; UH = University hospital. Participants indicated their level of agreement to the statements on a scale seven-point rating scale from 1 = I strongly disagree to 7 = I strongly agree.

Appendix D *Manipulation Text for the Two Message Appeal Conditions (Study 2)*

Others-benefit
"Empower PEOPLE'S health, share data! Data sharing can transform healthcare and provides benefits to all people. With the help of data sharing, you will directly enhance people's lives. Everyone will make better informed decisions. Everyone will get a better treatment. This will increase well-being of all people."

Self-benefit
"Empower YOUR health, share data! Data sharing can transform healthcare and provides benefits to you personally. With the help of data sharing, you will directly enhance your quality of life. You will make better informed decisions. You will get a better treatment. This will increase your well-being."

Appendix E *Manipulation Text for the Two Message Endorser Credibility Conditions (Study 3)*

Recently, [U.S. President Donald Trump /U.S. Representative for Global Health Diplomacy Deborah Birx, M.D.] has encouraged people to provide personal health data to support organizations like the ["MWC General Hospital"/ "MWC Pharma"] in their efforts. In a recent press conference, [President Trump/ M.D. Birx] highlighted the importance of up-to-date and real health data as supporting information for experts in health and medicine.

Notes: Terms in brackets [ ] are the two variants of the manipulation of the requesting entity that were randomly assigned to the participants. Depending on the experimental condition participants either read one or the other of the variant descriptions

Appendix F *Variables for Credibility and Domain-specific Expertise (Study 3)*

Items	**DB**				**DT**			
	PC		**UH**		**PC**		**UH**	
Credibility. How much do you agree with the following statements? XX is	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Dependable	5.01	1.34	4.82	1.54	3.76	2.23	4.11	2.21
Honest	4.97	1.57	4.81	1.54	3.70	2.21	4.18	2.29
Reliable	5.14	1.37	4.89	1.59	3.74	2.32	4.16	2.20
Sincere	5.03	1.41	4.92	1.56	3.99	2.22	4.08	2.18
Trustworthy	4.05	1.47	4.93	1.60	3.69	2.26	3.97	2.16
Expert	2.18	1.13	5.28	1.59	3.69	2.25	3.87	2.19
Experienced	5.54	1.15	5.49	1.40	4.02	2.18	4.30	2.20
Knowledgeable	5.63	1.11	5.35	1.37	3.91	2.28	4.38	2.13
Qualified	5.71	1.24	5.34	1.34	3.88	2.21	4.27	2.21
Skilled	5.40	1.39	5.29	1.43	3.93	2.18	4.23	2.06
Friendly	5.04	1.46	4.89	1.46	3.74	2.03	4.18	2.01
Likeable	4.94	1.38	4.96	1.46	3.77	2.09	4.11	2.21
Warm	4.94	1.38	4.87	1.49	3.74	2.26	3.99	2.12
Approachable	5.12	1.34	4.95	1.53	3.94	2.21	4.05	2.18
Domain Expertise. With regards to Covid-19, I would consider XX to be ...	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
An expert	5.60	1.23	5.16	1.51	3.67	2.34	3.84	2.29
Experienced	5.60	1.13	5.42	1.55	3.58	2.22	4.00	2.27
Knowledgeable	5.47	1.17	5.44	1.34	3.67	2.22	3.95	2.17
Qualified	5.55	1.16	5.47	1.32	3.59	2.21	3.91	2.21
Skilled	5.62	1.17	5.44	1.33	3.58	2.16	3.96	2.22

Notes: XX in the item was substituted with either President Donald Trump or M.D. Deborah Birx depending on the experimental condition; DB = Deborah Birx; DT = Donald Trump; PC = Pharmaceutical company; UH = University hospital; M = Mean; SD = Standard Deviation.

Appendix G *Manipulations Texts for Disease Severity and Diagnostic Method (Study 4)*

Vignette for Diagnostic Method (AI) and Disease Severity (low)

Please imagine that you have health issues and seek medical advice.

Please read the scenario on the next page and imagine how it feels to be affected by the disease, and what kind of decisions you would make in such situation. We have set a **minimum reading time** to make sure that you have enough time to read what is described in the scenario.

Just recently, you noticed a change of a mole on one of your arms. While having a shower, you again check the mole on your skin. It has grown since the last time you checked it and the borders look irregular. Also, the color of the mole looks quite abnormal to you. To find out whether this development is normal or abnormal, you seek medical advice.

You decide to use a **real-time medical decision support aid** that is based on **artificial intelligence (AI) technology**. It is a certified and approved Internet-based application. First, you answer **various disease-relevant questions** about your health condition and your symptoms. Second, you upload a picture of your skin. Then, the software applies a sophisticated algorithm in agreement with standard medical guidelines to come to a diagnosis. On the next page, you will see a brief description of how the diagnosis is derived:

The medical decision support aid is a computing system that uses machine learning to provide an accurate diagnosis and treatment recommendation. Experts developed this system to process and learn from existing health information databases. When you input your health information into the system, it compares your input with these databases. The databases contain all filed data – medical records and images from various clinical sources such as laboratories, cancer centers, academic medical centers, and hospitals from the US population. The analytics engine pulls out relevant insights from all available cases of patients with similar symptoms to yours. It also considers medical evidence from textbooks and scientific journals. This computing system then matches the best outcome and practices from cases like yours to determine its recommendation. In particular, the algorithm was trained to detect skin cancer from images using deep learning. This is when the computers process hundreds of thousands of labeled disease images until they can classify the images on their own. As a result, the computing system is able to quickly classify patterns in your medical imaging and match it to similar cases to provide you with a diagnosis.

Diagnosis:
In your case, the artificial intelligence (AI) medical aid **diagnoses early-stage, slow-growing skin cancer**.
It is at **stage 0** (the very lowest of five stages), which means that abnormal cells are found but they have not spread into nearby normal tissue yet. The severity of the disease is the lowest possible and it is quite unlikely that it moves to the next stage.

Treatment:
The aid's medical **recommendation** is a combination of topical therapy and oral medication. The topical therapy is a treatment where the anti-cancer medicine is applied directly on the skin once or twice a day for several weeks. When put directly on the skin, the medication kills abnormal cells and destroys the lesion. Additional oral pill intake blocks the growth of the cancer cells.

Vignette for Diagnostic Method (physician + AI) and Disease Severity (low)

Please imagine that you have health issues and seek medical advice.

Please read the scenario on the next page and imagine how it feels to be affected by the disease, and what kind of decisions you would make in such situation. We have set a **minimum reading time** to make sure that you have enough time to read what is described in the scenario.

Just recently, you noticed a change of a mole on one of your arms. While having a shower, you again check the mole on your skin. It has grown since the last time you checked it and the borders look irregular. Also, the color of the mole looks quite abnormal to you. To find out whether this development is normal or abnormal, you seek medical advice.

You decide to see a **medical doctor** who is known for the usage of **artificial intelligence technology** when diagnosing patients. You go to the doctor's office. It is a certified and approved office, and the usage of the Internet-based machine learning application is certified and approved as well. First, you answer **various disease-relevant questions** about your health condition and your symptoms. Second, you show the doctor your skin and he/she then uploads your data into the software. Then, the medical doctor assesses your skin and, with the software that applies a sophisticated algorithm, comes to a diagnosis, using his or her expertise based on standard medical guidelines in addition to the computer aid. On the next page, you will see a brief description of how the diagnosis is typically derived:

The medical decision support aid is a computing system that uses machine learning to provide an accurate diagnosis and treatment recommendation. Experts developed this system to process and learn from existing health information databases. The medical doctor uses his/her best knowledge for diagnosis and treatment. He/she has been trained by experts and learned throughout his/her work life as a technology-savvy medical doctor. In combination, they form a human-and-machine expert system.

When the doctor inputs your health information into the system, it compares the input with health information databases. These databases contain all filed data – medical records and images from various clinical sources such as laboratories, cancer centers, academic medical centers, and hospitals from the US population. The analytics engine pulls out relevant insights from all available cases of patients with similar symptoms to yours. It also considers medical evidence from textbooks and scientific journals. This computing system then matches the best outcome and practices from cases like yours to determine its recommendation. In particular, the algorithm was trained to detect skin cancer from images using deep learning. This is when the computers process hundreds of thousands of labeled disease images until they can classify the images on their own. As a result, the computer is able to quickly classify patterns in your medical imaging and match it to similar cases to provide a diagnosis. The doctor then checks this diagnosis against the background of his/her expertise (previous experience; state-of-the-art evidence; contrasting possible explanations and eliminating less probable explanations).

Diagnosis:
In your case, with the help of an artificial intelligence medical aid, the medical doctor **diagnoses early-stage, slow-growing skin cancer**. It is at **stage 0** (the very lowest of five stages), which means that abnormal cells are found but they have not spread into nearby normal tissue yet. The severity of the disease is the lowest possible and it is quite unlikely that it moves to the next stage.

Treatment:

The doctor's medical **recommendation** is a combination of topical therapy and oral medication. The topical therapy is a treatment where the anti-cancer medicine is applied directly on the skin once or twice a day for several weeks. When put directly on the skin, the medication kills abnormal cells and destroys the lesion. Additional oral pills intake blocks the growth of the cancer cells.

Vignette for Diagnostic Method (physician) and Disease Severity (high)

Please imagine that you have health issues and seek medical advice.

Please read the scenario on the next page and imagine how it feels to be affected by the disease, and what kind of decisions you would make in such situation. We have set a **minimum reading time** to make sure that you have enough time to read what is described in the scenario.

Just recently, you noticed a change of a mole on one of your arms. While having a shower, you again check the mole on your skin. It has grown since the last time you checked it and the borders look irregular. Also, the color of the mole looks quite abnormal to you. To find out whether this development is normal or abnormal, you seek medical advice.

You decide to see a **medical doctor** and go to the doctor's office. It is a certified and approved office. First, you answer **various disease-relevant questions** about your health condition and your symptoms. Second, you show the doctor your skin. Then, the medical doctor assesses your skin and comes to a diagnosis, using his or her expertise based on standard medical guidelines. On the next page, you will see a brief description of how the diagnosis is typically derived.

The medical doctor uses his/her best knowledge to provide an accurate diagnosis and treatment recommendation. He/she has been trained by experts and learned throughout his/her work life as a medical doctor. The medical doctor compares your case with cases that he/she has dealt with in the past and he/she is aware of – based on medical records and images from various clinical sources such as laboratories, cancer centers, academic medical centers, and hospitals from the US population. The medical doctor filters relevant insights from all available cases of patients with similar symptoms like yours. He/she also considers medical evidence from textbooks and scientific journals. He/she then derives the best outcome and practices. In particular, the medical doctor is trained to detect skin cancer via contrasting possible explanations and eliminating less probable explanations. The medical doctor uses his/her knowledge until he/she can classify the disease. He/she is able to quickly classify patterns, match the disease with similar cases, and provide you with a diagnosis.

Diagnosis:
In your case, the medical doctor **diagnoses mid-stage, rather fast-growing skin cancer**.
It is at **stage II** (0 and I indicate low severity), which means that abnormal cells are found and have started to spread into nearby normal tissue. The severity of the disease is high and it is quite likely that it moves to the next stage.

Treatment:
The doctor's medical **recommendation** is a combination of topical therapy and oral medication. The topical therapy is a treatment where the anti-cancer medicine is applied directly on the skin once or twice a day for several weeks. When put directly on the skin, the medication kills abnormal cells and destroys the lesion. Additional oral pill intake blocks the growth of the cancer cells.

Appendix H *Variables for Compliance Intentions (Study 4)*

Items	HI						LO					
	P		P-AI		AI		P		P-AI		AI	
Compliance Intentions	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Please indicate how likely you would follow the medical recommendation of the doctor.	6.24	1.12	6.22	1.12	6.04	1.15	6.33	.87	6.22	.94	5.79	1.32
What is the probability that you will stick to the recommendation of the doctor?	6.09	1.28	6.06	1.36	5.96	1.25	6.32	.90	6.17	1.18	5.65	1.37
How closely would you follow the recommendation of the doctor?	6.29	1.20	6.14	1.21	6.12	.97	6.28	.92	6.28	.88	5.88	1.40
How likely will there be a positive outcome when sticking to the recommendation?	5.74	1.14	5.68	1.14	5.75	1.01	5.96	.96	6.06	.94	5.59	.99
How certain is it that you would achieve positive outcomes when sticking to the recommendation?	5.41	1.16	5.43	1.25	5.32	1.27	5.63	1.11	5.92	.85	5.23	1.10
What is the probability of having positive outcomes when you follow the recommendation?	5.67	1.24	5.65	1.19	5.76	.85	6.00	.83	5.95	1.19	5.53	1.08

Notes: HI = High disease severity; LO = Low disease severity; P = Physician; P-AI = Physician plus AI; AI = Artificial intelligence tool; M = Mean; SD = Standard Deviation.

Appendix I *Variables for Social Presence and Innovativeness (Study 4)*

Items	**HI**						**LO**					
	P		**P-AI**		**AI**		**P**		**P-AI**		**AI**	
Social Presence There is a sense of…	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
human sensitivity in the process	5.51	1.06	5.39	1.19	3.85	2.14	5.68	1.18	5.44	1.18	3.64	2.06
human warmth in the process	5.32	1.10	5.22	1.12	3.72	2.13	5.50	1.16	5.37	1.26	3.51	2.11
sociability in the process	5.16	1.23	5.07	1.37	3.93	2.08	5.42	1.30	5.31	1.20	3.79	2.09
personalness in the process	5.50	1.09	5.38	1.22	4.07	1.97	5.58	1.16	5.51	1.09	3.92	1.94
human contact in the process	5.74	1.01	5.50	1.22	3.77	2.10	5.87	.91	5.47	1.21	3.44	2.08
Innovativeness There is a sense of…	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
technological advancement in the process	5.51	1.28	6.18	.86	6.07	.93	5.51	1.36	6.10	.97	6.05	1.04
innovativeness in the process	5.09	1.43	6.00	.99	6.08	.90	5.58	1.15	5.99	1.08	5.95	1.00
state-of-the-art knowledge generation in the process	5.50	1.28	6.14	.97	6.00	.85	5.63	1.11	6.01	.96	5.95	1.00

Notes: HI = High disease severity; LO = Low disease severity; P = Physician; P-AI = Physician plus AI; AI = Artificial intelligence tool; M = Mean; SD = Standard Deviation

Eidesstattliche Erklärung

Ich erkläre an Eides statt, dass ich die bei der Fakultät für Wirtschaftswissenschaften der TUM zur Promotionsprüfung vorgelegte Arbeit mit dem Titel:

Paving the Way for Medical AI:
Consumer Response to Artificial Intelligence in Healthcare

am Lehrstuhl für Sport- und Gesundheitsmanagement unter der Anleitung und Betreuung durch Prof. Dr. Jörg Königstorfer ohne sonstige Hilfe erstellt und bei der Abfassung nur die gemäß § 6 Ab. 6 und 7 Satz 2 angebotenen Hilfsmittel benutzt habe.

- Ich habe keine Organisation eingeschaltet, die gegen Entgelt Betreuerinnen und Betreuer für die Anfertigung von Dissertationen sucht, oder die mir obliegenden Pflichten hinsichtlich der Prüfungsleistungen für mich ganz oder teilweise erledigt.
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Die öffentlich zugängliche Promotionsordnung der TUM ist mir bekannt, insbesondere habe ich die Bedeutung von § 28 (Nichtigkeit der Promotion) und § 29 (Entzug des Doktorgrades) zur Kenntnis genommen. Ich bin mir der Konsequenzen einer falschen Eidesstattlichen Erklärung bewusst

Mit der Aufnahme meiner personenbezogenen Daten in die Alumni-Datei bei der TUM bin ich einverstanden.

München, 28.12.2020 ……………………………………………………………

Michaela Söllner