Patients' Acceptance of New Procedures in Healthcare

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For Morten Renner, Heike & Ralf and Johannes Gesk, Christa & Heiner Müller

Morten’s Family and my Friends

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List of Abbreviations

AI .... Artificial Intelligence
EPPM .... Extended Parallel Processing Model
HBM .... Health Belief Model
HIS .... Health Information System(s)
HPV .... Human Papillomavirus
ITF .... Integrated Theoretical Framework
LM .... Linear Regression Model
MAE .... Mean Absolute Error
MRI .... Magnetic Resonance Imaging
mRNA .... Messenger Ribonucleic Acid
PMT .... Protection Motivation Theory
PRT .... Psychological Reactance Theory
RAA .... Reasoned Action Approach
RQ .... Research Question
SRMR .... Standardized Root Mean Square Residual
TAM .... Technology Acceptance Model
TPB .... Theory of Planned Behavior
TRA .... Theory of Reasoned Action
UTAUT2 .... Unified Theory of Technology Acceptance and Use 2
VIF .... Variance Inflation Factors

1 Synopsis

1.1 Introduction

New procedures in healthcare are of particular interest to physicians, patients, healthcare systems because of their promise to improve effectiveness and quality (Loftus et al., 2020; Longoni et al., 2019). There are various applications of new procedures, ranging from new treatment methods to AI-based applications (e.g., Bahadori et al., 2020; Eberhardt & Ling, 2021). Thus, we divide the new procedures into two areas. On the one hand, there are new digital procedures. These are medical treatments in which the focus is predominantly on new technologies such as artificial intelligence (AI)-based applications (e.g., Zheng et al., 2021). The difference between AI-based applications and other software applications is that AI applications have intelligent capabilities such as problem solving, perception, reasoning, and communication (Leyer & Schneider, 2019; Russel & Norvig, 2010; Rzepka & Berger, 2018). Here, technology performs the treatment. On the other hand, there are new non-digital procedures. These are new medical treatments such as new treatment methods or vaccines (e.g., Tenforde et al., 2021). Here, the human mainly performs the treatment. These new non-digital procedures include COVID-19 vaccines, as a new procedure was used to develop the vaccines (Tenforde et al., 2021).

New procedures should aim to maximize benefits while minimizing risks (e.g., AI-HLEG, 2019). Through the application of new procedures, individuals can prevent disease or mitigate the consequences of disease (Bahadori et al., 2020; Say et al., 2006). Patients weigh harm against benefit, especially when making medical decisions (Resnik, 2004; Say et al., 2006). This may be due to the fact that the individual's own body becomes an output or a feature of the output (Say et al., 2006). With digital procedures, patients must be willing to process their own data to promote their health (Longoni et al., 2019). Individuals or patients have e.g., the ability to monitor their health via different tracking apps (e.g., Bahadori et al., 2020).With non-digital procedures, patients must be willing to have the new treatment method performed on their bodies. In addition, patients are less likely to make medical decisions (especially far-reaching ones) than other decisions (Armstrong et al., 2001). Hence patients' acceptance is of immense importance. This leads to the first research question:

Which factors influence patients' intention to use new procedures in healthcare?

The results of the first research question will now be applied to different situations and decisions. There are several situations in which decisions need to be made, some of which are critical to surviving (Lahsen & Ribot, 2022; Maglio et al., 2016; Useem et al., 2005). This also applies in medical decisions. Different situations and decision types may influence utilization intention to use and medical decision-making. Thereby, patients' intentions to use new procedures across different decision types have not been investigated in depth. Decision types include point-in-time decisions (Larsson Ivanov et al., 2022), decisions during ongoing actions (Ulbrich & Gail, 2021), sequential updating decisions (Armstrong et al., 2001), and framed decisions (Akl et al., 2011). This leads to the second research question:

What are the effects of relevant variables related to new procedures in healthcare on various decisions?

For answering these two research questions, we investigate individual decision behavior under the aspects of the critical realism research philosophy presented in Section 1.2. Further, the presented research questions are addressed by designing an integrated theoretical framework (ITF), combining different theories of healthcare, information systems, and psychology (see Section 1.3.1). The ITF from Section 1.3.1 is applied to test the patients' acceptance of new procedures in healthcare under various decision types at different risk levels (see Section 1.3.2). Section 1.4 presents the results of these examinations. Afterwards, the results are discussed in Section 1.5. The findings from the results and discussion are presented in Section 0 as theoretical and managerial implications. The limitations and approaches for future research are given in Section 1.7.

1.2 Research Philosophy

This dissertation is based on the principles of critical realism theory according to Bhaskar (2013). The principles of critical realism theory are used to explain patients' acceptance of new procedures in healthcare. Understanding the individual decision behavior of patients with respect to new procedures could lead to a higher intention to use. A high intention to use leads to acceptance of new procedures in healthcare (Floyd et al., 2000). New procedures enable more efficient treatment and prevention options, which offers further optimization opportunities for patients, physicians, and healthcare systems (e.g., Chau & Hu, 2002; Cheung et al., 2019; Van der Schaar et al., 2021).

To understand patients' acceptance, it is first necessary to study observable events in the "empirical" domain using mixed methods. Mixed methods are suitable for information system research (Morse, 2016; Venkatesh et al., 2013). According to Morse (2016), there is a core component that is a complete method for addressing the research question(s). This core component is self-contained and could be published (Morse, 2016). In this dissertation, the core component is presented deductively as theory testing research in the form of an ITF (see Section 1.3.1). In addition to the core component, there is the supplementary component, which represents the methodological strategy. The supplementary component is itself incomplete and cannot stand alone. It is to be seen as an extension of the investigation of the core component (Morse, 2016). In this dissertation, individual decision behavior with the four decision types represents the supplementary component (see Section 1.3.2).

Furthermore, the observations are used to understand the patient's intention to use based on the underlying mechanisms and laws in the domain “actual”. Here, the underlying mechanisms and laws of the observations were used to rule out other possible explanations (see Section 1.4). Furthermore, we used a deductive core component, which means that the core component has to be completed before the investigation of the supplementary component can begin. This design has the advantage that aspects can be adjusted between individual investigations (Morse, 2016). Therefore, the ITF changes or adapts elements in the course of the studies (see ITF in Section 2, Section 3, Section 4, and Section 5). From these findings, we can derive, discuss, and thus better understand patients’ acceptance of new procedures in healthcare in the domain "real" (see Section 1.5). This division of the different domains of patients’ acceptance of new procedures in critical realism theory is illustrated in Figure 1.

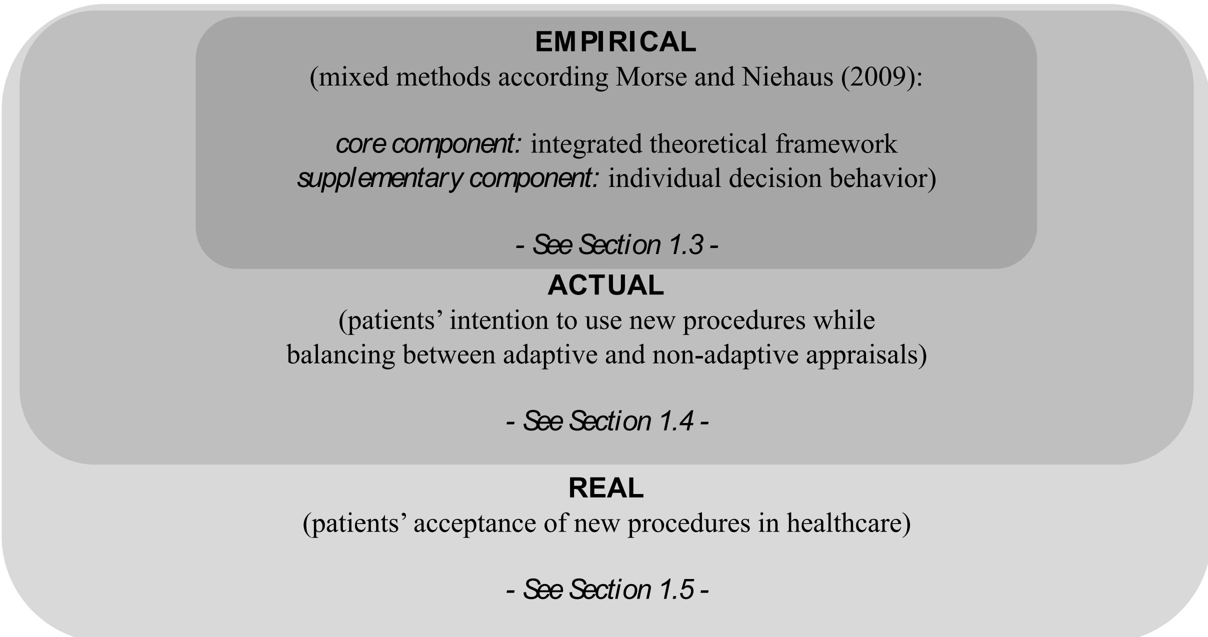

Figure 1: Acceptance of new procedures in healthcare according to the critical realism theory Figure according to Mingers (2004)

1.3 Research Concept

1.3.1 Research Framework

Since this dissertation aims to identify relevant variables that influence the intention to use new procedures in healthcare, several relevant theories can be identified. First, all theories in the different disciplines of healthcare, information systems, and psychology that deal with intention to use were highlighted. Then, appropriate variables were compiled to better understand the intention to use new procedures in healthcare. Finally, we selected the most commonly used theories from healthcare, information systems, and psychology for acceptance testing with the same or similar variables to obtain a comprehensive understanding. The following theories from different perspectives were used and are shown in Table 1.

From a healthcare perspective, the Health Belief Model (HBM) was developed by Hochbaum (1958), Rosenstock (1960) and Rosenstock (1974a). HBM seeks to understand the acceptance of healthcare. The model focuses on perceived threat and behavioral evaluation of preventive actions as the two drivers of intention to engage in healthy behaviors (Vassallo et al., 2009). Protection Motivation Theory (PMT) is an evolution of HBM and was conceptualized by Rogers (1975) and Floyd et al. (2000). The theory states that intention is mainly influenced by adaptive and non-adaptive appraisals (called duality approach). Thus, the duality approach allows the (potential) disease and its potential intervention to be appraised simultaneously as two reference objects influencing intention and behavior. The Extended Parallel Processing Model (EPPM) is another variant of the duality approach. The EPPM does not add any new elements to the PMT, but provides a somewhat different grouping of variables (Storey et al., 2008; Witte, 1994). It also claims that adaptive behavior is more cognitive, whereas non-adaptive behavior is more emotional (Popova, 2012; Witte, 1994).

From a technology perspective, approaches include the Unified Theory of Technology Acceptance and Use 2 (UTAUT2) (Venkatesh et al., 2012) and the Technology Acceptance Model (TAM) in its various variants (e.g., Chau & Hu, 2002; Davis et al., 1989; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000; Venkatesh et al., 2012). UTAUT2 and the TAM variants are popular in information systems. However, TAM and UTAUT2 are regularly used outside of information systems research (Williams et al., 2012). Another problem with the many TAM variants is that the practice of freely modifying models and theories makes results inconsistent and difficult to compare and aggregate (Tate et al., 2015). In addition, UTAUT2 includes all of the variables in the TAM (Venkatesh et al., 2012).

From a general psychological perspective, the Theory of Planned Behavior (TPB) has been more widely used to understand the intention to use outside of information systems research (Ajzen, 2020). TPB has been promoted similarly to the Theory of Reasoned Action (TRA), while both have been combined into the Reasoned Action Approach (RAA). The main difference from earlier versions of the TPB is that the RAA includes beliefs that form an attitude, norm, or perceived behavior control (Fishbein & Ajzen, 2010). It is designed to explain individual behavior in general, independent of health-related issues. In addition, Psychological Reactance Theory (PRT) was developed by Brehm (1966). PRT describes individuals' reactions to perceived threats to current or future freedom (Ghazali et al., 2018; Ngafeeson & Manga, 2021; Rosenberg & Siegel, 2020).

Healthcare Perceptive	**Technology Perspective**	**Psychological Perspective**
• Health Belief Model	• Unified Theory of Technology Acceptance 2	• Theory of Planned Behavior
• Protection Motivation Theory	• Technology Acceptance Model	• Psychological Reactance Theory
• Extended Parallel Processing Model		• Reasoned Action Approach

Table 1: Theories used in the integrated theoretical framework

1.3.2 Research Process

This dissertation focused on individual decision behavior (Miner Jr, 1984; Rapoport & Wallsten, 1972) because the research questions relate to patients' intentions to use new procedures. Rapoport and Wallsten (1972) divided individual decision behavior into two groups: single-stage decision-making and multi-stage decision-making (see Figure 2).

Single-stage decision-making occurs when the individual has to make a single decision (Rapoport & Wallsten, 1972). Therefore, a point-in-time decision is a decision that the individual makes once. Thus, there is only one decision moment (Larsson Ivanov et al., 2022).

Multi-stage decision-making deals with multiple decisions over a period of time and can be divided into two subgroups: dynamic and sequential (Rapoport & Wallsten, 1972). In dynamic multi-stage decision-making, the previous decision influences the upcoming decision (Rapoport & Wallsten, 1972). This dissertation focused on two types of decisions in dynamic multi-stage decision-making. First, decision during ongoing actions considers decisions that need to be made while performing a specific behavior (Ulbrich & Gail, 2021). Second, decisions are called sequential updating decisions if there is a certain amount of time between two or more decisions (Armstrong et al., 2001; Larsson Ivanov et al., 2022). The timing of a previous decision determines the timing of the subsequent decision (Larsson Ivanov et al., 2022). In contrast to dynamic multi-stage decision-making, in sequential multi-stage decision-making the previous decisions do not influence the upcoming decision (Rapoport & Wallsten, 1972). This subgroup includes, e.g., optional stops and changes of mind (Rapoport & Wallsten, 1972). Changes of mind can be triggered by additional information (Tversky & Kahneman, 1981). These decisions are called framed decisions. The framing effect has been studied outside of healthcare and shows that individuals behave differently depending on how the information is framed (Cunneen et al., 2019; Ho, 2021; Tversky & Kahneman, 1981). In the case of medical decisions, the framing effect has also been studied many times and shows that in addition to the framed information, the context also influences the patient's behavior (Akl et al., 2011; Peng et al., 2013). In Figure 2, the different decision types are classified into groups and subgroups of individual decision behavior.

Individual Decision Behavior

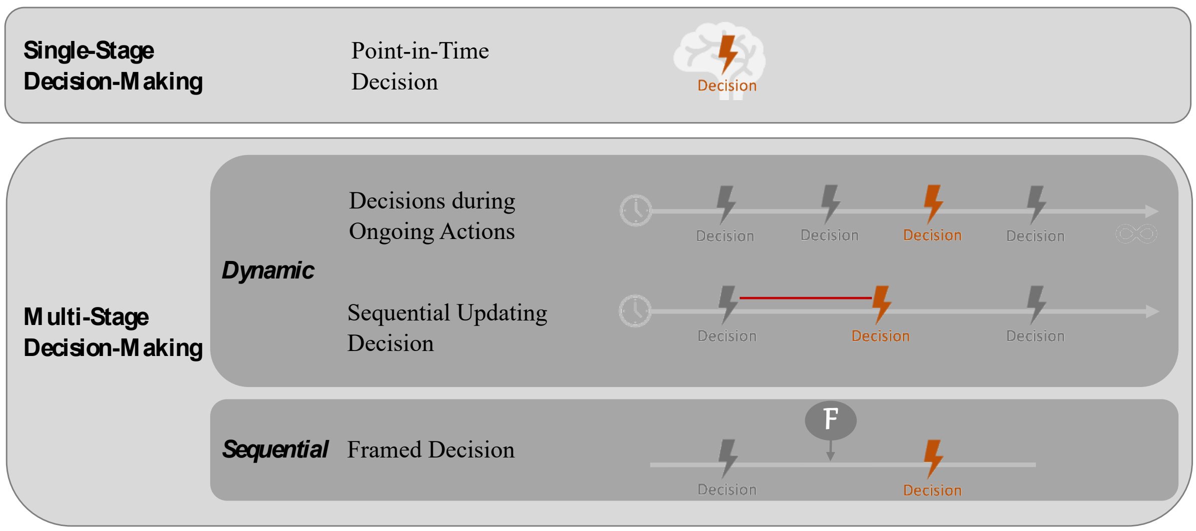

Figure 2: Individual decision behavior

Notes. F = Framing

In addition to different types of decisions, different levels of risk can also influence decision behavior (Rapoport & Wallsten, 1972). According to theory of risk of Pollatsek and Tversky (1970), there are three basic assumptions about risk: (1) risk is a property of options (some of which are risky) that affects the choice among them; (2) options can be ranked according to their risk; and (3) the risk of an option is related to the variance of its outcomes.

Based on the first and second basic assumptions, this dissertation assigned a risk to the trials depending on the disease and sorted them into low-, medium-, and high-risk groups (see Figure 3). The fourth study considers the third basic assumption of risk presented, namely that the risk of an option is related to the variance of its outcomes. The variance, in conjunction with other properties of the option, can represent the probability of maximum loss (Pollatsek & Tversky, 1970; Rapoport & Wallsten, 1972). Especially in medical decisions, the risk of loss should be minimized (Logsdon et al., 1989; Say et al., 2006). Figure 3 shows in which section the individual decision behavior of the respective decision type is examined and at what level of risk it is examined.

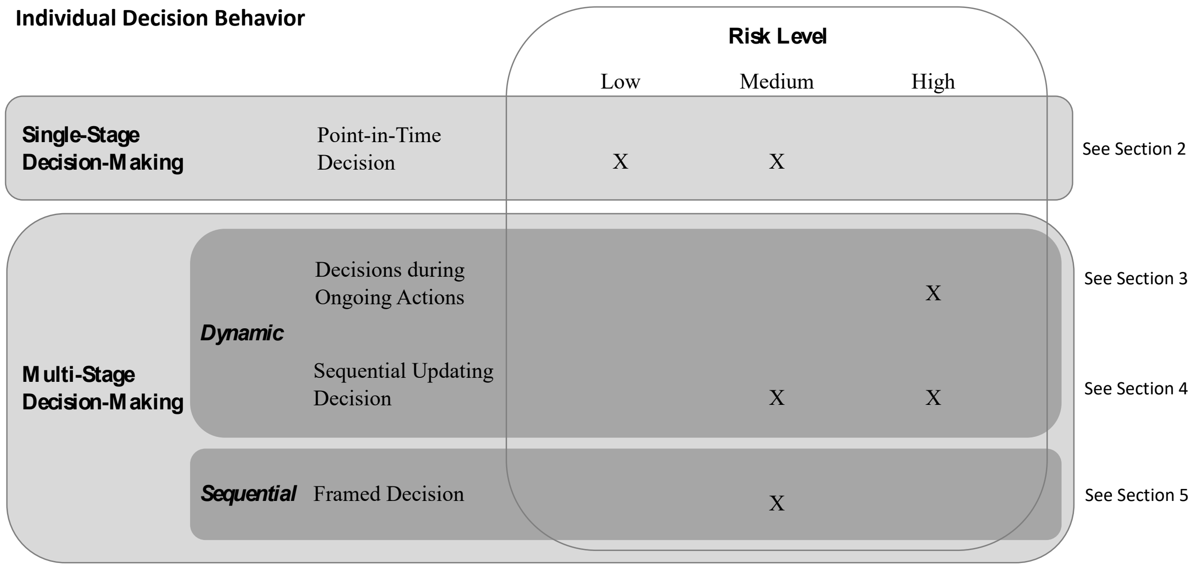

Figure 3: Schematic overview of the dissertation's structure

(Combination of individual decision behavior with risk levels)

1.4 Research Results

1.4.1 Health Information Systems: Potential Users balancing Adaptive and Maladaptive Appraisals[1]

In order to determine the patients' intention to use new procedures, we developed an ITF that combines the theories presented in Section 1.3.1 from healthcare, information systems, and psychology. The duality approach examines the trade-off between adaptive and non-adaptive appraisals and their influence on intentions to use new procedures. Adaptive appraisals consider

[1] The article was presented at the Forty-Second International Conference on Information Systems, Austin 2021 and is published in Proceedings of the International Conference on Information Systems (ICIS) 2021.

aspects in the context of interventions to alleviate or cure a disease. Non-adaptive appraisals reflect aspects related to the disease. In this way, it will be investigated which factors influence the intention to use new procedures in healthcare and which variables are ultimately relevant for the formation of the intention to use.

We applied the ITF to the context of emerging AI-based health information systems (HIS) in surgeries. In particular, AI-based applications may have great potential in the medical field (Loftus et al., 2020; Zhou et al., 2020) and are a new procedure that is already partially used in healthcare (Rauschecker et al., 2020). Therefore, this procedure is suitable for investigating the intention to use new digital procedures in healthcare.

We investigated AI-based HIS for surgery using a scenario-based questionnaire. Since the decision for or against surgery is made once, this decision situation is considered a point-in-time decision (Armstrong et al., 2001). At the same time, we investigated the influence of different risk levels by hypothetically and randomly assigning the probands to two different diseases. The diseases were non-life-threatening and curable, respectively (Goh et al., 2020; Suo et al., 2020). For the low-risk study, we chose cataract because the surgery is frequently performed and has a low error rate (Gutiérrez-Robledo et al., 2021). For the medium risk study, we chose ankle arthritis because the surgery is rarely performed and therefore has a high error rate (Norvell et al., 2018). None of these conditions are high risk because they are not life-threatening if not operated on and only cause severe limitations in daily life (Goh et al., 2020; Suo et al., 2020).

To determine a difference in the intention to use completely new and partially new digital procedures, there was one surgery with only AI-based HIS and one surgery with AI-based HIS assisting the physician for each disease. As a control, a physician-led surgery was chosen to determine potential differences between known, partially new, and completely new surgeries for each disease.

Questionnaires were developed and completed by 496 participants. The results showed that the higher the proportion of new procedure in surgery, the more individuals relied on adaptive appraisals to make the decision. Furthermore, there was no significant difference between low and medium risk levels.

Based on this research, we were able to provide empirical support for our ITF. Further, the results show that the intention to use the new procedure decreases slightly with increasing abstraction. Hence, the focus of decision-making is on adaptive appraisals as the level of abstraction increases due to the new procedure.

1.4.2 The Threat of New Health Information Systems for Established Services[2]

To investigate the patients' intention to use new procedures in decision during ongoing actions, we applied the ITF of Gesk et al. (2021) in the context of an AI-based HIS for diabetes support. This study is also suitable for investigating the intention to use new digital procedures, as it is an AI-based application (Loftus et al., 2020).

Therefore, we investigated the intention to use AI-based HIS in relation to a service for individuals with type 1 diabetes Mellitus. Diabetes is a lifelong, incurable disease, which is why individuals with diabetes make daily decisions about whether or not to use the AI-based HIS (Leyer & Iloska, 2021). Therefore, this service is part of the decision during ongoing actions (Ulbrich & Gail, 2021). We also investigated whether individuals with diabetes want to continue with their previous disease-based routine or use the new AI-based HIS for better blood glucose control. At the same time, diabetes is life-threatening if left untreated or if blood glucose levels are not maintained (Leyer & Iloska, 2021), so the risk of this decision was considered high.

In this study, we wanted to determine whether the level of abstraction of new procedures influences the intention to use them (Carrera et al., 2020). We hypothetically developed three different services that were randomized to 197 actually type 1 Diabetic Mellitus patients. In one service, blood glucose control is provided only by the AI-based application to study the decision-making of diabetes patients with new digital procedures. In another service, blood glucose control is provided by a physician with AI-based support. In this service, the level of abstraction is lower because the known is mixed with the unknown. As a control group in this study, blood glucose monitoring was performed by a physician only to examine the impact of new procedures in the other services on decision-making.

The results show that only when the service is known to a physician, the intention to use is formed by balancing adaptive and non-adaptive appraisals. As soon as the level of abstraction is increased by adding new procedure, the diabetes patients focus only on the adaptive appraisals. The mean intention to use is approximately the same for all three services. Based on these results, the ITF of Gesk et al. (2021) can also be applied to actual patients and decision

[2] The article was presented at the 17th International Research Symposium on Service Excellence in Management (QUIS17) Jan. 12th-14th 2022, Valencia and is published in Proceedings of the QUIS17 – The 17th International Research Symposium on Service Excellence in Management.

during ongoing action with high-risk. This allows for a better understanding of the introduction of new digital procedures as healthcare services.

1.4.3 The Disease or the Vaccination: What is More Important when Deciding Whether to Vaccinate?[3]

To determine patients' intention to use new procedures in sequential updating decisions, we applied the ITF of Gesk et al. (2021) to the context of COVID-19 vaccination. Since early 2020, the global population has been threatened by the novel COVID-19 virus (Wong et al., 2021). Vaccination against COVID-19 was the only long-term measure that could lead to herd immunity (Chung et al., 2021). The vaccine was produced using a new process (messenger ribonucleic acid (mRNA) vaccination) that had not been used for any other vaccine (Edwards & Carfi, 2022; Tenforde et al., 2021). Therefore, the COVID-19 vaccine lacked evidence of potential long-term side effects, safety, and duration of protection (Fernandes et al., 2021). For this reason, COVID-19 vaccination is suitable as a new, non-digital procedure in healthcare.

The COVID-19 virus can cause severe to fatal disease (da Silva & Pena, 2021; Raveendran et al., 2021). In the absence of antibodies and immune memory against COVID-19, the probability of such a course is high. Vaccination with COVID-19 allows individuals to build antibodies and reduce the risk of severe or fatal disease (Cox & Brokstad, 2020). Individuals without antibodies had a high risk of a severe to fatal course (Chung et al., 2021). Therefore, the decision to vaccinate these individuals is a high-risk one. Individuals with pre-existing antibodies are at moderate risk because vaccine protection wanes over time (Cox & Brokstad, 2020; Mathieu et al., 2021).

The COVID-19 vaccination is voluntary and should be repeated additional times due to the decline in vaccine protection (Mathieu et al., 2021; Sasaki et al., 2022). Therefore, this decision is considered a sequential updating decision. We conducted this study in December 2021, when the third COVID-19 vaccination was already available. We asked 172 twice-vaccinated and 82 unvaccinated individuals about their intention to receive the third or first COVID-19 vaccination.

The results show that the twice-vaccinated individuals included both adaptive and non-adaptive appraisals in their intention to vaccinate. For the unvaccinated, only the adaptive appraisals have an influence on their vaccination decision. This study conducted further evidence for the

[3] The article is currently under review for publication in Social Science and Medicine journal.

ITF of Gesk et al. (2021). The results also show that the model can be applied to sequential updating decisions with medium and high risk. These findings shed light on which factors public institutions need to address in future interventions in order to obtain specific behavior from the target group.

1.4.4 Framed Information in Medical Decisions for AI-based HIS: Balance between Adaptive and Non-Adaptive Appraisals[4]

Much research has been done on how framed information affects intention to use (e.g., Peng et al., 2013). To gain a deeper understanding, we investigated patients' individual decision behavior using the ITF of Gesk et al. (2021) in the context of radiological diagnostics using an AI-based application. As it is an AI-based application, this study is also suitable for studying the intention to use new digital procedures (Loftus et al., 2020; Rauschecker et al., 2020).

In this study, radiological evaluation of magnetic resonance imaging (MRI) scans was to be performed to rule out serious brain diseases. As this was only an evaluation and not a (near-body) treatment, we classified this decision as medium risk.

629 participants were hypothetically free to choose a radiologist or an AI-based application to evaluate their brain MRI images. After making the decision, the probands were randomly given either negatively framed (error-rate) or positively framed (success-rate) information about the performance of the physician and AI-based HIS. These information were based on the actual accuracy of brain MRI in radiological diagnostics (see Rauschecker et al., 2020). Subsequently, we gave the probands again the opportunity to choose a rating form.

The results show that positive framed information have a negative influence, but negative framed information have a positive influence on the intention to use HIS. However, the difference in decision-making between the positively framed information and the negatively framed information is very small. For all decisions, we noticed that the decision arose largely from the adaptive appraisals. Here, attitudes toward HIS and perceived efficacy were key variables for intention to use.

Based on this study, we showed that ITF of Gesk et al. (2021) can provide a deeper understanding of already known effects such as framing. This deeper understanding may help to make educational discussions between doctor and patient more effective. Thus, this could

[4] This article is in preparation for submission.

increase the patients' acceptance regarding AI-based HIS which allows physicians to spend more time with patients.

1.5 Discussion

The dissertation investigated patients' acceptance of new procedures in healthcare through the individual decision behavior of patients regarding their intention to use. Different theories from the fields of healthcare, information systems, and psychology were combined in an ITF to cover different aspects of the disciplines and theories. The ITF was applied to different decision types with different levels of risk. These were studied in the context of both new digital and new non-digital healthcare procedures.

The successful application of the ITF of Gesk et al. (2021) to different study contexts shows that a blend of interdisciplinary theories such as healthcare, informatic systems, and psychology provides a broader understanding of individual decision behavior. Especially for medical decisions, a deep understanding of decision-making is necessary to increase patients' acceptance. With the help of the ITF and the investigations, important insights were gained to address the research questions.

The results of this dissertation show that (1) decision-making changes as the percentage of new procedure increases. The new procedures dominate decision-making, which can be seen in the focus on variables of adaptive appraisals.

Further, (2) different decision types and risk levels have mostly an insignificant impact on patients' acceptance, and the results show that decision-making changes as the percentage of new procedures increases. These results partially support the findings of Carrera et al. (2020) that as the level of abstraction of a decision increases, so does the intention to use it. However, there are differences between decision types.

For point-in-time decisions and decision during ongoing actions, decision making is similar, even with respect to different risk levels. The higher the proportion of new procedure, the more the decision is made on the basis of adaptive appraisals. This effect is even more pronounced for decision during ongoing action. This could be due to the fact that individuals are familiar with their condition and decisions are made on the new object, in this case a new procedure.

For sequential updating decisions, the focus on adaptive appraisals decreases when individuals have already chosen the new procedure in previous decisions. This shows that only new and abstract objects are focused on in decision-making. However, when things are only new and no longer unknown, individuals again balance their decisions from a combination of adaptive and non-adaptive appraisals.

For framed decisions, different individual decision behavior is observed than for the other decision types. Whereas in the other investigations, decision-making became increasingly focused on adaptive appraisals as the proportion of new procedure increased, in this study there was no difference in decision-making between the groups with different percentage of new procedure. Further, framed information had no significant effect on the level of intention to use. In contrast, studies such as Peng et al. (2013) and Akl et al. (2011) show that the framing effect has an impact on the level of intention to use in healthcare.

The results of these studies can also be applied to other decisions outside of healthcare that affect one's well-being or body (Say et al., 2006). Another area where decisions are made about one's well-being or body is in emergency services such as firefighting. Firefighters are in dangerous and stressful situations on a daily basis where they must make the right decision quickly to save or prevent harm (Useem et al., 2005). Unlike the decision-making of a patient, firefighters have to make many and varied decisions in a situation, most of which affect other people (Maglio et al., 2016). Especially when using new equipment and mission tactics (Useem et al., 2005), individual decision-making should be studied to ensure the health of all involved. Another area where decisions are made about one's well-being or body is autonomous mobility, such as an autonomously driven car (e.g., Cunneen et al., 2019; Ho, 2021). Here, individuals cede responsibility for their own body's integrity to AI-based procedure.

1.6 Theoretical and Managerial Implications

In order to determine patients' acceptance of new healthcare procedures, the research questions were investigated using critical realism theory. In the empirical domain, observational experiences were conducted using the mixed-methods structure of Morse (2016). Hence, the core component was an ITF and the supplementary component was the individual decision behavior with different decision types. The ITF combines interdisciplinary theories from healthcare, information systems and psychology. This ITF was applied to different types of individual decision behavior. This enabled us to identify important mechanisms of individual decision behavior in the domain "actual" (see Section 1.2). These mechanisms provide information on how to increase patients' acceptance of new procedures in healthcare.

The following theoretical implications can be derived from this dissertation. First, understanding the intention to use new procedures in healthcare can be investigated through the ITF. The duality approach with adaptive and non-adaptive appraisals combined with variables from the disciplines of healthcare, information systems and psychology. This allows a deeper understanding of decision-making in health-related situations. The ITF and the corresponding questionnaire can also be used for other types of examinations in healthcare as well. With minor adaptations (e.g., replacing the threat of disease with the threat of not knowing), the ITF can also be used for decision-making in non-healthcare contexts.

Second, assigning decisions to a scheme has proven useful in clarifying differences in individual decision behavior. In Rapoport and Wallsten (1972)'s single-step decision-making, point-in-time decisions are considered. Rapoport and Wallsten (1972)'s dynamic multi-stage decision-making classifies decisions during ongoing actions and sequential updating decisions. Framed decisions belong to the sequential multi-stage decision-making. This scheme can also be applied outside the healthcare context in studies of decision behavior. Using this classification, individual decisions can be grouped and compared.

Third, the results of this dissertation show how different characteristics of the disease and the new procedure affect decision-making. For the disease, characteristics such as life-threatening, curable, frequent treatment, and risk level were changed. Small differences are evident. For the new procedure, characteristics such as digital-based and framed information were changed. Significant differences have been found, with the framed information having the greatest impact on decision-making.

In addition, practical implications can be given based on the findings of the dissertation. First, during the initial explanation of the new procedure, a detailed explanation should be given, especially regarding efficacy. In addition, fears about the new procedure should be identified during the discussion and addressed through further explanation. In addition, family members should be present at this discussion to help the patient make a decision.

Second, in general, the physician's educational discussions with the patient should focus on the aspects of the disease and the method of treatment. However, for high-risk and medium-risk decisions, the physician should also emphasize the consequences of not treating the patient. This can minimize the likelihood that individuals will decide against treatment because of uncertainty about the treatment.

Third, physicians, as well as marketing agencies for medical applications, should be careful to adapt information to be contextually directed. In addition to explanations of new procedures, aspects of the disease should be the focus of education.

Forth, fear of the new procedure is an important variable in medical decision-making. Clinics and marketing agencies for medical applications could ensure that the new procedure is presented transparently. For AI-based procedures, the trustworthy AI approach should be considered and the current ethical guidelines for trustworthy AI of the European Commission (e.g., AI-HLEG, 2019) should be followed.

Fifths, clinics should introduce new procedures gradually. Patients are more likely to choose the new procedure for their treatment if they have repeated choices. This would allow patients to become familiar and comfortable with the new procedure.

1.7 Limitations and Future Research

Patients' acceptance of new procedures in healthcare was determined on the basis of intention to use. However, intention to use does not necessarily equate to actual use. This phenomenon is known as the intention-behavior gap (Fishbein & Ajzen, 2010). Therefore, we cannot make any statements about the actual behavior of individuals based on these investigations. Further research may fill the research gap.

In the point-in-time decision, decision during ongoing action, and sequential updating decision, probands had the opportunity to choose only for or against the procedure offered. In the framed decision, probands had the opportunity to choose between a physician and the new procedure for both treatment options. Thus, in the framed decision, individuals had higher perceived behavioral control, which is a variable of perceived efficacy. Perceived efficacy is a fundamental component of medical decision-making in all studies of this dissertation. It is possible that the differences in decision-making would also decrease with an increasing proportion of new procedures (see Section 2, Section 3, Section 4), if individuals had a choice between several examination methods. Further research is therefore needed in this area.

Further, we not only manipulated decision types, risk levels, and digital versus non-digital procedures, we also varied the application of the new procedure. In the studies with point-in-time decisions, decisions during ongoing action, and sequential updating decisions individuals had direct physical contact with the new procedure. In contrast, the framed decision study did not involve physical contact with the individual. This needs to be re-examined.

Another limitation is that we did not examine how the probands perceived the risk in each situation. It is possible that the individual's perception of risk does not match our risk classification. This area therefore requires further research.

Moreover, risk perception in the sequential updating decision may have been increased by more than two years of media exposure, especially among the twice-vaccinated. Among the unvaccinated, the influence of conspiracy theories may have significantly influenced the medical decision (Eberhardt & Ling, 2021). Therefore, it would be interesting to replicate the decision-making process with similar reference objects that do not have a strong media presence when the decision is sequentially updated. Further research may be the answer to this research gap.

Further, this dissertation examined medical decisions that probands were asked to make decisions for themselves. Therefore, based on these studies, we cannot draw conclusions about individual decision behavior when making decisions for others, such as minor children. More research is needed in this area.

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2 Health Information Systems: Potential Users balancing Adaptive and Maladaptive Appraisals[5]

Tanja Sophie Gesk, Johannes Wichmann and Michael Leyer

Abstract

As digital technologies are increasingly important in healthcare, it is important to determine whether and why potential users intend to use such health information systems (HIS). Several theories exist however mainly focusing on either healthcare or information systems aspects next to general psychological theories. We develop an Integrated Theoretical Model allowing to analyze the duality of adaptive and maladaptive appraisals and their influence on the intention to use HIS. We apply the Integrated Theoretical Model to the important domain of AI-based HIS for surgeries in order to gather empirical support. The results show that the model can be applied successfully and provide important insights which factors are relevant depending on the novelty of the AI-based HIS. We contribute to information systems literature by highlighting the importance to integrate aspects regarding disease and technology in a joint model. Practitioners can use the instrument to identify the most promising reasons for adoption.

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2.1 Introduction

Using digital technology in healthcare applications is a topic with increasing popularity (Longoni et al., 2019). New digital technologies offer opportunities to provide more connected healthcare services for individuals. Health information systems (HIS) for individuals cover healthcare services that are directly provided or applied on individuals. Hence, options for application of health information systems (HIS) are extensive, ranging from software applications also embedded in smart devices like smartphones and wearables that help to identify diseases and to support individual treatment faster (Tanwar et al., 2020) (e.g. self-learning insulin pumps for individuals with diabetes or even a Corona tracking app) to health services provided to individuals that include the usage of specific HIS (e.g. an automated laser surgery in a hospital). Individuals can make use of such HIS to prevent diseases proactively or to lessen the negative consequences of diseases by adopting devices or services containing a specific HIS (Bahadori et al., 2020).

Especially, artificial intelligence (AI) based HIS have proven to be effective in healthcare, e.g. regarding the analysis of radiologic pictures (Zheng et al., 2021), AI-based HIS are different to traditional HIS by being able to perform self-learning and thus to improve its own algorithms (Zhou et al., 2020). As such, it is able to adapt to new situations and to decide based on the improved algorithms. This is particularly important for healthcare applications, as actions are performed while the patient's possibility to influence those measures is limited and decisions are made based on experience and the evidence found (Loftus et al., 2020). Besides the development of AI, it is important to investigate whether patients intend to use such a HIS, as it is updating (and improving) its own algorithms and thereby less transparent concerning the decision-making.

The intention to use HIS can be determined using two different perspectives. First, the health perspective is important according to which an individual has to decide whether he/she is going to accept a certain treatment and/or show health-supporting behavior (termed adaptive appraisals) or is reluctant to a treatment and showing behavior that is fostering the disease (maladaptive appraisals) (Gücin & Berk, 2015). Second, the information systems perspective which targets whether an individual is accepting a certain type of system/technology (e.g., Karahanna et al., 1999). From a healthcare perspective, one can identify Health Belief Model, Protection Motivation Theory and Extended Parallel Process Model, from a technological perspective Unified Theory of Technology Acceptance and Use 2 is relevant and psychological theories consist of Psychological Reactance Theory and the Reasoned Action Approach.

Summing up the different theories, models, and approaches, it becomes evident that they share common elements while these are partly arranged in different ways, which is partly justified that they are descended from each other.

While there have been various applications mixing healthcare and technology using theories from each domain (e.g., Cheng & Jiang, 2020; Gao et al., 2015), the discussion is mainly separated in different streams of literature. Hence, there has not been an approach that combines relevant variables of healthcare and technologies on a theoretical level that investigate the intention to use AI in HIS. To fill this gap, we ask two research questions. First, on a theoretical level, which variables are influencing the intention to use HIS to treat diseases? Second, on the applied level of AI-based HIS, which variables are relevant and how strong is their impact on the intention to use AI-based HIS used for surgeries?

To address our first research question, we adopt the duality approach of separating adaptive and maladaptive appraisals from healthcare theories and identify the most relevant shared variables. In addition, the resulting integrated theoretical model integrates social influence as a third line of argumentation that influences variables both within adaptive and maladaptive appraisals following the argumentation of RAA. Moreover, in order to address our second research question, we apply the model to the context of using AI-based HIS in the context of operations. We focus on two prominent types of surgeries. One is cataract operations, an operation that is conducted with standard procedures for a large amount of individuals (GBE-Bund, 2017; Goh et al., 2020), the other one is arthrosis, which is following less standardized protocols as it is riskier and undertaken not that often (GBE-Bund, 2012; Suo et al., 2020). The results surveying individuals with their intention to use different forms of AI-based HIS for surgeries (also compared to purely human surgical teams) show that adaptive appraisals become the main predictor with an increasing AI role. This indicates that the more AI dominates the intervention, the less individuals think of the (potential) disease.

The paper is organized as follows: We start with a review of relevant theories from healthcare and information systems and combine relevant elements in our integrated theoretical model. This is followed by the application of the framework to the domain of using AI in surgeries. We then describe material and method of the quantitative study and report the results. The results are discussed within the application domain as well as regarding the integrated theoretical model. The paper closes with theoretical as well as practical implications and limitations followed by future work.

2.2 Theory

2.2.1 Review of Theories from Healthcare and Information Systems

As our research aims to identify relevant variables that influence the intention to use information systems in healthcare-related situations, different relevant theories can be identified. First, all the theories in the different disciplines of healthcare, information systems, and psychology that consider intention to use were highlighted. Then, matching variables were put together to better understand the intention to use new technologies in the healthcare field. The following theories from the different perspectives were used. From a healthcare perspective, health belief model (HBM) was developed by Hochbaum (1958) and Rosenstock (1960); Rosenstock (1974a) to understand the acceptance of health prevention. The model focuses on perceived threats and behavioral evaluation of preventive actions as the two drivers of the intention of showing healthy behavior (Vassallo et al., 2009). Protection motivation theory (PMT) is a further development of HBM and was conceptualized by Rogers (1975) and Floyd et al. (2000). The theory states that intention is mainly influenced by adaptive and maladaptive appraisals (duality approach) which allow to rate the (potential) disease and the potential intervention simultaneously as two distinct reference objects influencing intention and behavior. Extended parallel processing model (EPPM) is another variation of the duality approach adding no new elements compared to PMT, but providing a slightly different grouping of variables (Storey et al., 2008; Witte, 1994). Moreover, it claims that adaptive behavior is more cognitive while the maladaptive behavior is more emotional (Popova, 2012; Witte, 1994).

From a technological perspective, approaches include the Unified Theory of Technology Acceptance and Use 2 (UTAUT2) (Venkatesh et al., 2012), the Technology Acceptance Model (TAM) in its various versions (e.g., Chau & Hu, 2002; Davis, 1989; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000; Venkatesh et al., 2012). While UTAUT2 and TAM variants are popular within the information systems discipline, we note that outside IS, although TAM and UTAUT2 are moderately well-cited (Williams et al., 2012), TPB is more widely used (Ajzen, 2020). Another issue with the many TAM variants is that the practice of freely modifying models and theories makes the results incommensurate and difficult to compare and aggregate (Tate et al., 2015). Further, UTAUT2 contains all variables of TAM.

From a general psychological perspective, TPB has been promoted similar to TRA while both have been combined in the Reasoned Action Approach (RAA). The main difference from previous versions of TPB is that RAA includes beliefs that form an attitude, norm or perceived control (Fishbein & Ajzen, 2010). It is dedicated to explain individual behavior in general independent of health-related topics. Moreover, psychological reactance theory (PRT) was developed by Brehm (1966) and describes the reaction of individuals to perceived threats regarding current or future freedom (Ghazali et al., 2018; Ngafeeson & Manga, 2021; Rosenberg & Siegel, 2020).

Prior studies that focus on integrating technology- and healthcare-related methods are numerous and consider different stakeholders, such as physicians (Chau & Hu, 2002) or patients (Ku & Hsieh, 2018), while integrating different theories, such as TAM and TPB (Chau & Hu, 2002); TAM extended with variables to measure IT acceptance (Moores, 2012); HBM combined with variables to ascertain the usefulness of the intervention and the intention to adopt it (Cheung et al., 2019); HBM and TAM (Ahadzadeh et al., 2015); TPB and HBM (Ku & Hsieh, 2018); TPB and PMT (Zhang et al., 2020); and UTAUT2 combined with PMT and privacy calculus theory (Gao et al., 2015). While privacy, standards, and liability concerns regarding AI-based tools and their use from consumers' perspective are already well-investigated (Esmaeilzadeh, 2020), the aforementioned integrated models cover parts of the identified theories but an integrated model that combines relevant variables of healthcare and technologies on a theoretical level to determine the intention to use AI in HIS is missing.

2.2.2 An Integrated Theoretical Model

Table 2 provides an overview on the main variables within the different theories, including synonyms of respective variables due to different naming's among the theories. Additionally, we harmonized the naming of some variables to increase comprehensiveness.

Variables of integrated theoretical model (reference(s)) (/synonym(s)(theory)(reference(s))) Definition in the integrated model	**HBM**	**PMT**	**EPPM**	**UTAUT2**	**RAA**	**PRT**
Maladaptive appraisals (Witte, 1994) (/fear control process (EPPM, Witte, 1994)) describe the individual's evaluation of the disease, as threats, that are composed of perceived severity and perceived susceptibility, fear, maladaptive rewards for maintaining the current behavior towards the disease, and the individual's attitude are determined			X			
Perceived severity (Rogers, 1975; Rosenstock, 1974b) refers to the likelihood an individual perceives towards coming down with the disease	X	X				

Perceived susceptibility (Rosenstock, 1974b) (/probability of occurrence (PMT, Rogers, 1975)) explains the vulnerability an individual perceives towards coming with the disease	X	X				
Maladaptive rewards (Floyd et al., 2000) (/maladaptive response rewards (PMT, Floyd et al., 2000)) reflect the benefits an individual receives by maintaining the current behavior towards the disease		X				
Fear (Disease) (Floyd et al., 2000; Rogers, 1975) (/perceived threats, leading to fear (HBM, Rosenstock, 1974b)/ magnitude of threat to freedom (PRT, Brehm, 1966)) measures the emotion "anxiety" an individual feels towards the disease	X	X	X			X
Attitude (Disease) (Brehm, 1966; Fishbein & Ajzen, 2010) reflects the stance an individual has towards the disease					X	X
Adaptive appraisals (Rogers, 1975; Witte, 1994) (/danger control process (EPPM, Witte, 1994)) describe the individual's evaluation of the HIS, as the perceived efficacy, that is composed of perceived HIS efficacy and perceived self-efficacy, fear, perceived norms that reflect opinions of others towards the HIS, and the attitude towards the HIS are measured		X	X			
Perceived HIS efficacy (Rogers, 1975; Witte, 1994) (/perceived benefits (HBM, Rosenstock, 1974a)/ response efficacy (PMT, Rogers, 1975) (EPPM, Witte, 1994) /effort/performance expectancy/perceived usefulness/hedonic motivation (Venkatesh et al., 2012)) refers to the effectiveness of the HIS and the benefits provided to the individual	X	X	X			
Perceived self-efficacy (Rogers, 1975; Witte, 1994) (/facilitating conditions (UTAUT2, Venkatesh et al., 2012)/ perceived behavioral control (RAA, Fishbein & Ajzen, 2010)) describes the degree of freedom an individual perceives while determining the intention to use an HIS		X	X	X	X	
Perceived norms (Fishbein and Ajzen 2010) (/social forces (HBM, Hochbaum, 1958)/ social pressure (HBM, Rosenstock, 1960)/ advice from others (HBM, Rosenstock, 1974b)/ verbal persuasion (PMT, Floyd et al., 2000)/ social influence (UTAUT2, Venkatesh et al., 2012)) explain the opinion of others towards the HIS	X	X		X	X	
Fear (HIS) (Brehm, 1966; Rogers, 1975) (/anxiety (UTAUT2, Venkatesh et al., 2012))		X		X		X

describes the emotion “fear/anxiety" an individual feels towards the HIS						
Attitude (HIS) (Brehm, 1966; Fishbein & Ajzen, 2010; Venkatesh et al., 2012) reflects an individual’s stance towards the HIS				X	X	X
Intention to use (Brehm, 1966; Fishbein & Ajzen, 2010; Venkatesh et al., 2012; Witte, 1994) (/likelihood of taking action (HBM, Rosenstock, 1974b)/ cues to action (HBM, Hochbaum, 1958; Rosenstock, 1974a)/ protection motivation (PMT, Floyd et al., 2000)) refers to an individual’s tendency about using the HIS	X	X	X	X	X	X
Abilities (HIS) (Fishbein & Ajzen, 2010) (/perceived ease of use/habits/experiences (UTAUT2, Venkatesh et al., 2012)) determines a degree of which the individual thinks that it can handle the HIS easily				X	X	
Perceived costs/barriers (HIS) (Floyd et al., 2000; Rosenstock, 1974a; Venkatesh et al., 2012) (/perceived costs (PMT, Floyd et al., 2000)/ (UTAUT2, Venkatesh et al., 2012)/ perceived barriers (HBM, Rosenstock, 1974a)) explain the obstacles that prevent an individual from using the HIS	X	X		X		

Table 2: Overview on variables in relevant theories

Summing up the presented theories, models, and approaches, it becomes evident that they share common elements (partly conceptualized differently) while these are partly arranged in different ways. However, the duality approach of separating adaptive and maladaptive appraisals is consistent from a healthcare perspective and thus also the fundamental line of argumentation in our integrated theoretical model. Hence, we utilize the two different reference objects (1) concerning a specific disease by investigating related maladaptive appraisals towards the disease in question and (2) regarding an adaptive appraisal of the HIS to encounter the disease. Figure 4 provides an overview of our integrated theoretical model.

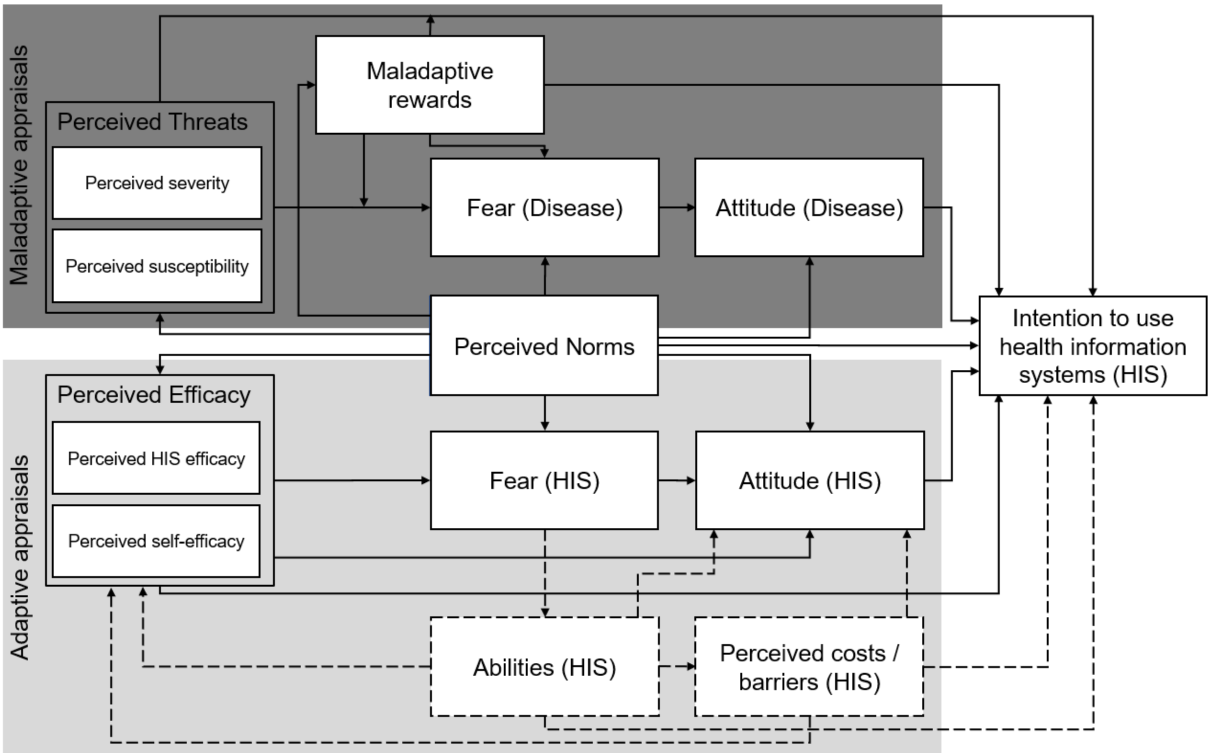

Figure 4: Integrated theoretical model describing the impact of maladaptive and adaptive appraisals on the intention to use HIS

Maladaptive appraisals start with perceived threats consisting of perceived severity and perceived susceptibility as a second order variable adapted from HBM according to Rosenstock (1960) and Rosenstock (1974a) and from PMT according to Rogers (1975). Perceived threats lead to fear regarding a disease and intention (as fear is an important variable that influences intention, according to PMT, Floyd et al., 2000; Rogers, 1975) while being moderated by maladaptive rewards (as an important mediator according to PMT, Floyd et al., 2000; Rogers, 1975). Attitude regarding the disease serves as a mediator between fear and intention as fear is a reactance to the perceived threats that influences the attitude towards the disease according to PRT (Brehm, 1966) and attitude being an important predictor for the intention to use according to Fishbein and Ajzen (2010). In addition, maladaptive rewards also have a direct influence on the intention to use HIS, which is supported by PMT (Floyd et al., 2000; Rogers, 1975).

Adaptive appraisals start with perceived efficacy (consisting of perceived HIS efficacy according to PMT (Rogers, 1975), EPPM (Witte, 1994) and HBM (Rosenstock, 1974b) as "perceived benefits") and perceived self-efficacy (Rogers, 1975; Witte, 1994; termed perceived behavioral control in RAA and facilitating conditions in UTAUT2) as a second order variable) which influences attitude regarding intervention (HIS), fear regrading a HIS and intention to use a HIS (as a combination of HBM, PMT, PRT and RAA, as explained above). While there have been different variables regarding efficacy (e.g., perceived ease of use, perceived usefulness, perceived costs/barriers), they could be integrated into the two variables within perceived efficacy from a conceptual perspective, as adaptive appraisals result from a positive difference between perceived efficacy and perceived inefficiency that are balanced by the individual (Floyd et al., 2000; Rosenstock, 1974b). However, as UTAUT2 disagrees with those perceptions, handling efficiencies and inefficiencies separately, we decided to consider the variables abilities (HIS) and perceived costs/benefits (HIS) conditional due to the application context the integrated theoretical model is applied to, following the recommendations of Fishbein and Ajzen (2010) and Venkatesh et al. (2012).

Social influence represented by perceived norms is included as a third line of argumentation that influences all other predictors in the model following mainly the argumentation of RAA. Such normative influences had been also part of HBM or PMT, but never been modelled explicitly as a core variable influencing both the maladaptive and adaptive appraisals. Further, perceived norms are important variables to predict technology adoption (e.g., Davis et al., 1989; Fishbein & Ajzen, 2010; Rogers, 1975; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000).

2.3 Application: Intention to Use AI for Surgeries

To provide specific, empirical support on understanding the reasons for intentions to use HIS, we apply the integrated theoretical model to the context of AI in surgeries. AI is an essential component of smart technologies in healthcare and is based on data mining. In this way, patterns and understandable implications can be identified from valid, novel, and potentially valuable data sets (Chung & Gray, 1999). Existing research in this domain covers various aspects using (if any) one of the prior presented theories. Palmisciano et al. (2020) investigated patients and their relatives' attitudes towards the use of AI in neurosurgery. As a result, most patients assume advantages in healthcare services by implementing AI as an assistant in neurosurgeries. Further, Longoni et al. (2019) examined patients' reasons for resistant behavior concerning the use of AI in healthcare with the perception that the most important reason for resting the use of AI is perceived personal uniqueness in terms of the respective individual's medical history. Thereby, individuals belief that AI would not be able to determine the most appropriate treatment for an individual with a non-average medical history (Longoni et al., 2019).

Using the integrated theoretical model, we derive specific hypotheses which are enriched with empirical research on the application level. First, the specific disease and the related threat appraisals towards the specific disease are reflected in perceived health threats of an individual due to a disease (Rogers, 1975). Those threat appraisals influence the fear an individual has concerning the disease (Krusemark & Li, 2011). Fear is an emotion that elicits anxious or emotional responses when performing a specific, fear-inducing behavior (Venkatesh et al., 2012). We thereby assume that individuals that are threatened concerning the disease will (a) feel the emotion of fear stronger (Krusemark & Li, 2011) and (b) have a higher intention to use a surgery with AI-based HIS to minimize or avert further negative health consequences (Floyd et al., 2000; Krusemark & Li, 2011). Consequently, our first hypothesis is:

H1: Perceived threats have (a) a positive influence on fear (disease) and (b) a positive influence on intention to use.

Additionally, the relations between perceived threats and fear as well as intentions may be influenced by rewards (as a positive outcome) that an individual receives for actively not pursuing a specific behavior (Vance et al., 2012) (e.g., not being impaired because of surgery with an AI-based HIS as the reward for actively not pursuing the intervention). Therefore, our second hypothesis is:

H2: Maladaptive rewards have a moderating effect on the relationship between perceived threats and (a) fear (disease) as well as (b) intention to use.

Moreover, maladaptive rewards increase the maladaptive behavior by not using surgeries with AI-based HIS (Floyd et al., 2000). Therefore, maladaptive rewards may directly influence the intention to use AI-based HIS (Vance et al., 2012). Hence, our third hypothesis is:

H3: Maladaptive rewards have a negative influence on intention to use.

Further, we assume that the attitude towards the disease, as an opinion that is positively or negatively related to a specific term (Venkatesh et al., 2012), is negatively influenced by the emotion of fear, which leads to the fourth hypothesis:

H4: Fear (disease) has a positive influence on attitude (disease).

Finally, as attitude (disease) is one of the most important drivers for the intention to use (Fishbein & Ajzen, 2010), a negative attitude will lead to a higher intention to use an AI-based HIS. Hence, our fifth hypothesis is:

H5: Attitude (disease) has a positive influence on intention to use.

Second, focusing on the adaptive appraisals using an AI-based HIS for surgery is the other reference object. At the beginning, the related perceived efficacy concerning the intervention describes the perception of an individual that the surgery in question supported or performed by an AI-based HIS is useful to encounter a specific disease (Venkatesh et al., 2012) and is one of the key elements related to the intention to use new technologies in healthcare (Sun et al., 2013). Furthermore, perceived efficacy is defined by a high level of self-efficacy and may lead to a higher willingness to use an intervention in question (Gao et al., 2015; Johnson et al., 2018; Sun et al., 2013). Surgery by an AI is, in most cases, more efficient, more accurate and less prone to error than humans as surgeons (Huang et al., 2020; Loftus et al., 2020). Following the duality approach of our integrated theoretical model, we consider fear and attitude as variables towards intention to use the AI-based HIS as well. Therefore, our sixth hypothesis is:

H6: Perceived efficacy has a negative influence on (a) fear (HIS) as well as a positive influence on (b) attitude (HIS) and (c) intention to use.

In studies of technology acceptance, fear has a major impact on attitudes toward the technology and their ultimate intention to use it (e.g., Huang et al., 2020; Palmisciano et al., 2020). Hence, we formulate the seventh hypothesis:

H7: Fear (HIS) has a negative influence on attitude (HIS).

Ultimately, in the case of technology acceptance, attitude plays a significant role in relation to intention to use (Fishbein & Ajzen, 2010; Palmisciano et al., 2020; Venkatesh et al., 2012). This leads to the following eighth hypothesis:

H8: Attitude (HIS) has a positive influence on intention to use.

Besides the duality approach, we assume that social pressure regarding a specific behavior defined as perceived norms (Ajzen, 1991; Gao et al., 2015) influence the variables in the integrated theoretical model. Previous studies have already shown a positive influence of perceived norms on the intention to use new technologies in healthcare (e.g., Miltgen et al., 2013; Sun et al., 2013). Hence, adaptive appraisals are presumably influenced in a positive way regarding AI-based HIS. Thus, perceived norms also are expected to make the maladaptive appraisals less attractive resp. considering them as more threatening as the pressure to overemphasize the potential threat of a disease increases. Therefore, our ninth hypothesis is:

H9: Perceived norms have, on the one side, a positive influence on (a) perceived threats, (b) fear (disease), (d) intention to use, (e) attitude (HIS), and (g) perceived efficacy, and on the other side, a negative influence on (c) attitude (disease), (f) fear (HIS), and (h) maladaptive rewards.

2.4 Material and Method

2.4.1 Application Scenarios

To gather empirical data, we used a scenario-based research design which includes manipulations and captures the decision of the individuals that are triggered through the scenarios (Webster & Trevino, 1995). This approach has already been shown to be relevant and applicable in the domain of analyzing the potential use of artificial intelligence (Leyer & Schneider, 2019). It has the advantage of analyzing the intention to use of artefacts that are not available in reality yet which is the case for automated AI-based HIS in surgery. We applied the integrated model to a 2x3 design with two typical types of potential diseases and three different types of interventions. Each individual received one randomly selected scenario with a full description of the disease and the option of surgery. The selection of adequate scenarios was based on the identification of diseases affecting a large number of individuals, are not fatal and allowing to construct a treatment situation involving different intensities of AI-based HIS that would directly affect individuals. As our participants had to solve an online questionnaire regarding an AI-based HIS that is not yet available, we decided that our scenario is not suitable for investigating the conditional variable "Perceived costs/barriers HIS" as the monetary costs, that are necessary to determine the perceived efficacy according to Venkatesh et al. (2012), are unknown.

From the disease perspective, one represented the disease "Cataract", for which the eye-vision of an individual slowly deteriorates. Cataracts are the leading cause of visual impairment worldwide (Goh et al., 2020). Generally, an intervention (e.g., surgery) to encounter the disease is not necessary but is recommended to significantly improve eye-vision. The surgery is standard with a low error rate. The other type of disease is "Arthrosis", with individuals feeling pain in their foot. Again, an intervention (e.g., surgery) is not necessary, but is recommended to enable pain-free walking (Suo et al., 2020). Here, the performed surgery is happening less frequently and thus there is also a higher chance of errors.

The intervention perspective covered two types of AI following the common separation into augmentation and automation (Raisch & Krakowski, 2021). AI would either perform the surgery on its own or AI would support a surgery team. To allow for comparison, we also include the case that a surgery team is performing an operation without AI support. Appendix A-1 provides an overview on the six resulting scenarios.

2.4.2 Questionnaire

According to the variables in the integrated model, we measured the following reflective variables by adapting the item templates of Fishbein and Ajzen (2010) to the context of surgeries in healthcare: intention to use (3 items), attitude (HIS) (5 items), perceived norms (4 items), perceived behavioral control (4 items), and attitude (disease) (5 items). Further, the reflective variables perceived response efficacy (3 items adapted from Taheri-Kharameh et al., 2020) and fear regarding HIS and Disease (3 items each adapted from Izard et al., 1993). The formative variables in the model, perceived vulnerability (4 items), perceived severity (7 items) as well as maladaptive rewards (3 items) were adapted from Boss et al. (2015) and Taheri-Kharameh et al. (2020). All items were measured on a 7-point Likert scale. In addition, self-developed single item control variables regarding experience with AI-based services, general computer skills and technical knowledge about AI were measured with a 5-point Likert scale next to basic demographics. The complete questionnaire can be found in Appendix A-2.

2.4.3 Sample

In order to recruit participants, we made use of the crowd working platform Clickworker which is similar to Amazon MTurk. On this platform, individuals in Germany between 18 and 70 years were addressed with our survey in April 2021. We gathered a convenience sample as everybody can be affected by the diseases and no one could have experienced an AI-supported surgery as such systems are not available yet. Participants were selected however based on their correct understanding of the assigned scenario and perceiving it as sufficiently realistic. To ensure a sufficient number of respondents for each scenario we gathered a total number of 496 respondents distributed among the scenarios as follows: Scenario 1: 78; Scenario 2: 83; Scenario 3: 77; Scenario 4: 101; Scenario 5: 74; Scenario 6: 83. Participants were given an introductory text about AI at the beginning of the survey if they were selected for a scenario involving AI. 40.7% of the participants were female, 59.1% male and 0.2% did not specify their gender. The average age is based on 37.08 years (SD: 12.07) and ranges from 18 to 70 years. The general computer skills have an average of 4.25 (SD: .744), the average experience level with AI-based services by participants is 3.06 (SD: .917), and technical knowledge about AI is 3.34 on average (SD: .850).

2.5 Results

We used partial least squares (PLS) to investigate the applied integrated theoretical model. We performed the bootstrapping procedure with 5,000 resamples in SmartPLS 3.3.3 (Hair et al., 2011). As Hair et al. (2011) described, the analysis of reflective and formative measurement models was conducted. First, all reflective variables fulfilled the criteria of indicator reliability since the values were above 0.7. Composite reliability was also confirmed as the values were above 0.7 and the average variance extracted is higher than 0.5 (Hair et al., 2011). Discriminant validity using the heterotrait-monotrait method was also given as the values were below 0.9 (Henseler, Ringle, et al., 2014).

Second, the formative variables were tested. Multicollinearity was given as the variance inflation factors were below 5 (Hair et al., 2011). The relative and absolute importance of the indicators were examined checking the significance of weights and loadings which were confirmed.

Third, the quality of the structural model was checked with the model fit using the standardized root mean square residual (Henseler et al., 2016). The values for saturated and estimated SRMR are below 0.1. Moreover, the blindfolding with a distance of 7 results in a positive Stone-Geisser Q^2. Therefore, the model is shown to be relevant for the progression of endogenous variables (Henseler et al., 2016).

We then use the model to calculate the results regarding the hypotheses for each scenario. The mean values of the intention to use the respective intervention are as follows: Scenario 1: Cataract, surgical team: 4.24; Scenario 2: Cataract, surgical team + AI: 3.69; Scenario 3: Cataract, AI only: 2.79; Scenario 4: Arthrosis, surgical team: 3.72; Scenario 5: Arthrosis, surgical team + AI: 3.42; Scenario 6: Arthrosis, AI only: 3.12. Figure 5 provides an overview highlighting the variables with significant path coefficients only.

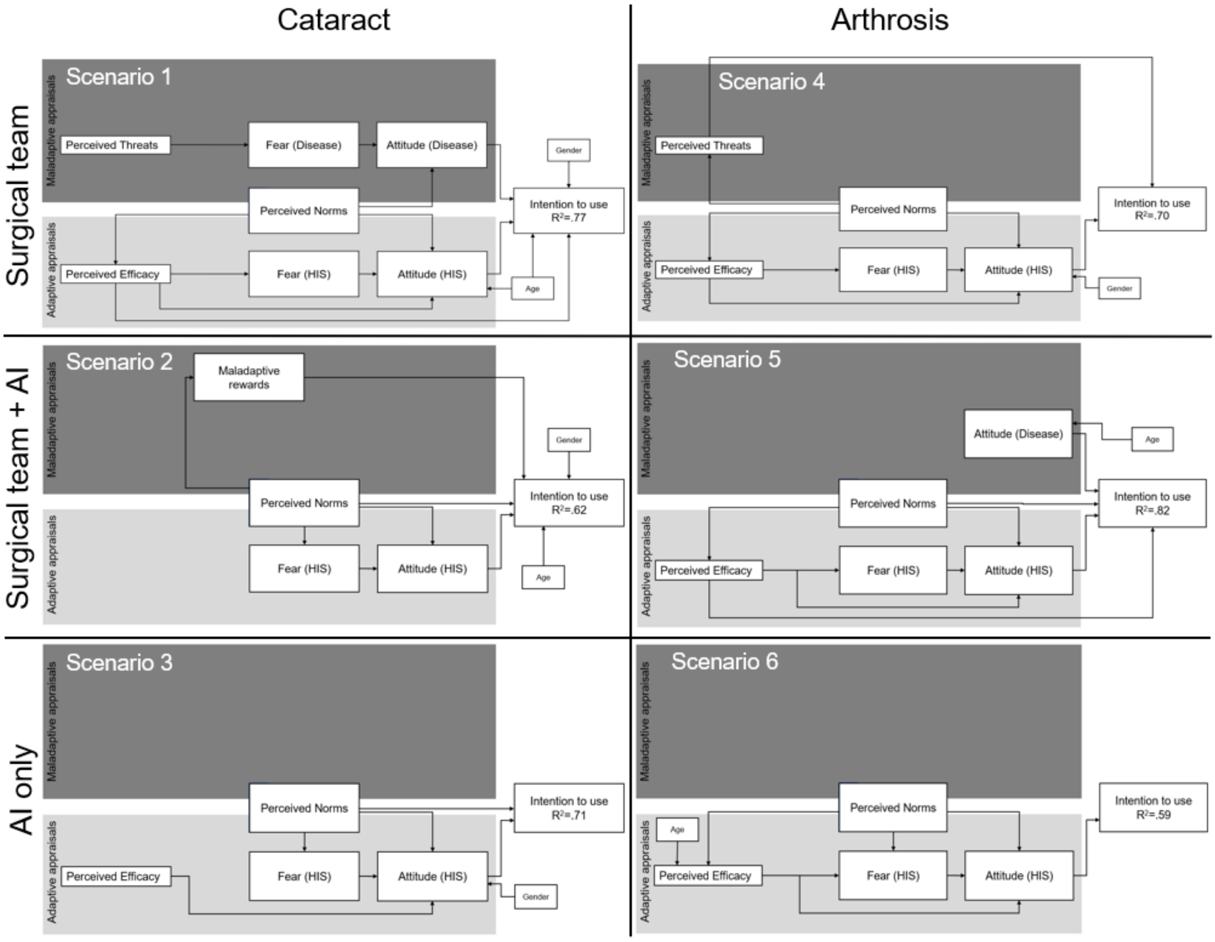

Figure 5: Results regarding hypotheses according to the scenarios

An overview on all path coefficients in the model according to the hypotheses can be found in Table 3 for each scenario.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
H1a: Perceived threats -> Fear (disease)	0.404^{***}	0.290^{*}	0.152	0.252^{**}	0.530^{***}	0.535^{***}
H1b: Perceived threats -> Intention to use	0.077	0.011	0.032	-0.096*	-0.024	-0.058
H2a: Perceived threats -> Fear (disease), Moderator: Maladaptive rewards	0.060	-0.234	-0.158	-0.041	-0.075	-0.135
H2b: Perceived threats -> Intention to use, Moderator: Maladaptive rewards	0.161	0.013	-0.099	-0.019	-0.056	0.123
H3: Maladaptive rewards -> Intention to use	-0.001	-0.172^{*}	-0.005	-0.104	-0.087	-0.074
H4: Fear(disease) -> Attitude (disease)	0.285^{***}	-0.058	0.309^{*}	0.051	0.082	-0.155^{*}

H5: Attitude (disease) -> Intention to use	-0.252*	-0.185	-0.034	-0.008	-0.132*	-0.129
H6a: Perceived efficacy -> Fear (HIS)	-0.397**	-0.177	-0.144	-0.198*	-0.370**	-0.221*
H6b: Perceived efficacy -> Attitude (HIS)	0.505***	0.067	0.363***	0.377***	0.388***	0.438***
H6c: Perceived efficacy -> Attitude (HIS)	0.670***	0.156	0.091	0.032	0.163*	0.130
H7: Fear (HIS) -> Attitude (HIS)	-0.155**	-0.413***	-0.483***	-0.202**	-0.283***	-0.288**
H8: Attitude (HIS) -> Intention to use	0.440**	0.438***	0.674***	0.731***	0.648***	0.643***
H9a: Perceived norms -> Perceived threats	-0.148	0.219	0.238*	0.202*	0.185	0.140
H9b: Perceived norms -> Fear (disease)	0.113	0.032	-0.014	0.277**	0.242**	-0.020
H9c: Perceived norms -> Attitude (Disease)	0.579***	0.113	-0.167*	0.033	-0.030	-0.312***
H9d: Perceived norms -> Intention to use	0.006	0.228*	0.198*	0.067	0.171*	-0.027
H9e: Perceived norms -> Attitude (HIS)	0.393**	0.451***	0.277**	0.381***	0.324***	0.351***
H9f: Perceived norms -> Fear (HIS)	0.163	-0.244*	-0.342**	-0.166	-0.141	-0.325**
H9g: Perceived norms -> Perceived efficacy	0.483***	0.457***	0.190	0.506***	0.590***	0.291**
H9h: Perceived norms -> Maladaptive rewards	-0.322*	-0.226*	0.007	-0.240*	-0.024	-0.037

Table 3: Path coefficients according to the hypotheses
(< .05, ** < .01, *** < .001, one-tailed tests)*

2.6 Discussion

Based on the results presented in the previous section, we can confirm that the duality approach and the variables applied from the integrated theoretical framework do matter, thus the results are adequately addressing the second research question. Thereby, our results reflect that, concerning our second research question, attitude and perceived norms are important predictors to determine the intention to use AI-based HIS for cataract, while attitude is the only significant predictor for the intention to use AI-based HIS for arthrosis.

When focusing on the different scenarios, the results regarding the full automation using AI-based HIS for surgeries (Scenarios 3 and 6), show that the maladaptive appraisals are not relevant. Adaptive appraisals referring to the AI-based HIS as a reference object are relevant and still providing a high explanatory contribution of intention to use the AI-based HIS. Given this result, we assume that using an AI-based HIS for a surgery without human intervention is an unknown, new healthcare technology and this uncertainty dominates the decision whether to use it. This is also reflected in the lowest average intention to use such a treatment compared to the other options. At the same time, this variable becomes so important that the disease itself is not a relevant variable in considerations anymore since all thoughts circle around the treatment. Our findings are supported, by e.g., Palmisciano et al. (2020) as they investigated attitudes of patients and their relatives towards the use of AI in neurosurgery. The authors determined in their study that the patients expressed concerns regarding autonomous surgical interventions. Patients stated that maintaining human interaction in medical treatments is very important for them and they want to keep humans in the loop at least. Consequently, the respective individual's perception about the efficacy of the AI-based intervention is an important variable to predict the intention to use, which is also supported by Esmaeilzadeh (2020) who investigated the use of AI-based HIS from a consumer's perspective.

When it comes to the option of using an AI-based HIS supporting a surgical team (Scenarios 2 and 5), our results show that variables from the maladaptive appraisals part are more relevant. Thereby, we assume that, in relation to a presumably missing ability of assessing a new form of HIS which leads to thinking about the HIS only, having a mixture of familiar and less known elements leaves room for considering the disease as well. This assumption is also supported by comparing the results with the control scenarios (1 and 4) containing the option of a surgical team without any AI-based HIS support. In these two scenarios, maladaptive appraisals are relatively more important indicating that they are considered next to the treatment in making a decision regarding the intention to use a surgical treatment. It has however to be noted that the result in Scenario 4 regarding H1b is opposite to the hypothesized direction. It might be that respondents think that a higher threat cannot be solved by a surgery conducted by humans and thus do not want to waste time on a surgery. Medical interventions from human surgical teams without AI-based HIS support are indeed the most current form of operation services (Ward, 2018) and thus individuals are presumably having the relatively best knowledge. Thereby, we consider interventions conducted by physicians as familiar interventions, as individuals are able to assess known treatments more easily. Interventions that are supported by new healthcare technologies (such as AI-based HIS) are unfamiliar interventions that are more complicated to assess by individuals. This assumption is supported by Longoni et al. (2019) who investigated the trustworthiness of physicians- and AI-based recommendations concerning a medical intervention. Their results show that individuals rely more on recommendations made by physicians than by AI as they assume that physicians are better suited for evaluating the respective individual medical history of an individual. Another study by Gao et al. (2015), who investigated wearable technology acceptance in healthcare provides additional support for this explanation. As wearable devices are commercially used and widely accepted in healthcare (Bahadori et al., 2020) and most individuals are familiar with utilizing wearable devices (and the required smartphone app, respectively), Gao et al. (2015) found that the intention to use is ascertained by perceived threats and perceived efficacy.

The perceived norms have an important role in all scenarios. It is however evident that the relevant others have a less positive view on AI-based HIS as well. Their influence is especially relevant to avoid negative effects from the disease to foster a negative attitude towards suffering from the disease for cataract as well as seeing the disease as a more severe threat for arthrosis. Further, as we compared our AI-based scenarios (3 and 6, see Figure 5), we determined that attitude and perceived norms were relevant for determining the intention to use an AI-based HIS for a cataract surgery, while only attitude was relevant for ascertaining the intention to use an AI-based HIS for an arthrosis surgery. Since the lifetime prevalence of cataract in Germany is more than twice as high as cataract (GBE-Bund, 2012, 2017), we conclude that the significance of perceived norms towards the intention to use for AI-based cataract surgeries is explained by it, as a more individuals suffer from cataract than from arthrosis.

Overall, however, we determined that the chosen scenarios lead to minor differences in terms of relevant variables, but the major differences are indeed following the dominance of the role of AI-based HIS. The normative influence is having a tendency to be against a stronger role of AI-based HIS and the intention to use it for surgeries are lower. Such an overall trend is explainable by investigating social healthcare robots. Initially, low acceptance by elder people concerning social healthcare robots was found by Broadbent et al. (2009), whereas a study conducted by Dziergwa et al. (2017) in 2017 showed acceptance of these robots. This could be related to the fact that robot- and AI-related issues have been increasingly addressed in society and thus those technologies became more popular. The technology was thus explained in more detail making it tangible for potential users as well as increasing the transparency of the consequences of AI-based interventions. Our integrated model indeed shows that such understanding is reflected in threats, efficacy and fear and the major levers can be identified upfront to a dissemination. Further, positive attitudes can be increased, for example, through training individuals with AI (Sit et al., 2020), which confirms our observation that attitude is an important predictor for intention to use. Hence, increasing knowledge about AI and frequent use of AI seems to lead to more convinced decisions about the possible intention to use AI, i.e. individuals who think that AI-based HIS are helpful also intend to use AI and vice versa.

2.7 Conclusion

2.7.1 Theoretical Implications

From a theoretical perspective, our study targets which variables are influencing the intention to use HIS to prevent or treat diseases as a typical challenge for HIS system providers, doctors, or healthcare systems. The empirical results provide support for our integrated theoretical framework, which allows us to make several contributions to information systems research. First, our results enhance understanding of the interaction between maladaptive and adaptive appraisals for the intention to use HIS by extending existing models from healthcare, highlighting their importance in our integrated theoretical model for HIS and applying it to AI-based HIS for surgeries. We extend theories from healthcare with elements from general psychological theories and information systems by adding the variable attitude, clarifying the role of perceived norms as well as integrating fear and attitude as dual variables (having disease and HIS as separate paths). Especially compared to theories in the field of information systems, we highlight the importance of the duality approach using two reference objects for analyzing the intention to use HIS. Second, we provide empirical support for the relevancy of our integrated theoretical model by applying it to AI-based HIS for surgeries; an important type of application in healthcare. The results regarding the explained variance show high values indicating a high predictive power, while the type of HIS leads to different importance of maladaptive and adaptive appraisals. Thus, we confirm the often proposed differentiation of self-acting HIS (due to AI) regarding augmentation and automation (Raisch & Krakowski, 2021) from the perspective of individuals in a healthcare context. It seems that the more self-acting a technology with reduced human contribution, the more relevant is the HIS-related path and the less relevant is the disease-related path. Third, we demonstrate the importance of analyzing pure forms of HIS in comparison to mixed forms and similar interventions without HIS being involved. Although the integrated theoretical model is focused on HIS it can also be used to allow for a comparison with a similar version performed by humans. The comparison allows to understand which elements of a HIS are influenced by the context and which ones are due to the perception of the HIS.

2.7.2 Practical Implications

Our findings also have different practical implications. Using, applying or providing HIS is an important topic for many actors in the healthcare sector. Healthcare institutions and/or doctors which invest in new technologies and provide services including such HIS should be aware that they have to focus on the disease and the intervention simultaneously. Especially the fear against the HIS is an important variable that has to be considered next to more rational arguments when patients have the choice regarding different options for operations. Our findings also support the findings of the study by Tran et al. (2019), which state that a large proportion of patients are willing to use AI-based HIS in medical treatments. A minority, on the other hand, would accept medical treatment only through AI and without human assistance (Tran et al., 2019). Therefore, we advise to use the integrated model to evaluate the most critical aspect regarding a new HIS and then focus on actions with regard to explainability and transparency which address the relevant aspect best. Our results on the applied level show that introducing a new HIS step by step in medical treatments as support is a helpful starting point, so that patients get used to the new technology and increase the intention to use. When it comes to the form of HIS, reconnaissance regarding the HIS requires more attention with self-acting AI and aspects regarding the disease require less attention. We thereby recommend healthcare providers to (a) be transparent in providing appropriate and comprehensive information concerning AI-based interventions. An increasing experience leads to a better attitude concerning AI-based interventions, resulting then in an increased intention to use AI-based interventions. We further recommend healthcare providers to (b) train their employees concerning the handling of AI-based interventions, as exercising raises the experience in AI-based interventions, which leads to an improved handling of AI-based interventions (Crockett et al., 2020; Ferrarese et al., 2016). Finally, improved AI-based interventions lead to higher intention to use among patients also potentially increasing positive word-of-mouth which has an additional positive effect according to the prominent positive role of perceived norms. Similarly, the above recommendations should be considered by HIS providers that aim at promoting their products and services either to healthcare institutions, doctors or individuals/patients. It is necessary to analyze the specific relevant variables to be able to determine whether the disease and/or the HIS should be targeted for advertisement. Even healthcare insurances should integrate the dual way of thinking and the specific relevance of maladaptive and adaptive behavior to assure that patients actually use the HIS they have been prescribed by doctors and paid by the insurance.

2.7.3 Limitations and Future Research

Our research is limited as follows. First, regarding the application of the theoretical model, we gather empirical data from scenarios in which participants should assume having the respective disease. Moreover, the scenarios refer to surgeries as a service which is provided at one point in time while a continuous usage of a HIS could lead to different influences of a disease and relevant HIS on intentions. Hence, other application areas might lead to different empirical effects and thus should be considered in future work to provide more empirical support for our integrated theoretical framework. Second, we did not consider the conditional variable "perceived costs/benefits" in our research, due to the application scenario. Further research should focus on that by using our integrated theoretical model to evaluate an HIS that is already existent. Third, the participants in our empirical study have an average experience of technology in general and AI while we cover individuals with a wide age range. While these variables did not have a significant impact, their variability is still limited and other groups with lower or higher experience might lead to different empirical results. Similarly, surveying participants from other cultural backgrounds might lead to different empirical results regarding respective scenarios. Third, the integrated theoretical model refers to a broad range of HIS regarding non-life-threatening diseases. To ensure an increased validity of our integrated model, it should be further evaluated by using life-threatening diseases instead. It could be that other variables become relevant for deciding that have not been covered by theories incorporated in the model. Fourth, we are well aware of the intention-behavior gap, but our integrated model targets the evaluation of HIS that do not exist on the market so far. Hence, we focus on intention, while knowing that behavior might be different. In accordance to the implementation of AI-based HIS that treat cataract and arthrosis, future research should focus on closing this gap by investigating the actual behavior.

The current study addresses an important topic relevant to both academic and practitioner audiences. Grounded in healthcare, information systems and psychological theories, our research shows promise for identifying the relevant variables leading to intentions to use novel HIS. Knowledge (or assumed familiarity) regarding a HIS is a relevant variable in terms of intention to use and should be considered to avoid rejection of HIS and a potential loss of investments. Promotions have to be carefully balanced between the disease and the intervention to ensure a high success. Continued examination of the relevancy of the dual paths as well as the normative opinion for novel HIS seem a promising avenue for future research.

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2.9 Appendix

2.9.1 A-1: Scenarios

Scenario 1 – 3 (Disease: Cataract; Frequency: Often; Error-prone: Low)

Your vision has declined over the past 3 years. Your ophthalmologist's diagnosis two days ago was early-stage cataracts. In cataracts, the otherwise clear lens becomes cloudy. Failure to treat it in the long term will lead to a further decline in vision. Retinal surgery can significantly improve your vision. Such surgeries are performed frequently and routinely, and as a result, complications and, in extreme cases, blindness of one eye rarely occur. In case of complications, the hospital is liable. Your only option is to get a surgery (Scenario 1) by a human surgical team, (Scenario 2) by a human surgical team supported by AI, or (Scenario 3) by an autonomous AI. In case of complications, the hospital is liable.

Scenario 4 - 6 (Disease: Arthrosis; Frequency: Rare, Error-proneness: High)

You have had pain in your right foot for 3 years. The diagnosis two days ago was osteoarthrosis of the ankle joint. In osteoarthrosis, the cartilage at the joints wears away. Failure to treat it will result in more severe pain when walking. Pain-free walking can be made possible by inserting a prosthesis. However, this operation is performed very rarely and therefore possible complications are unclear, but in extreme cases stiffening of the joint may be necessary. In case of complications, the hospital is liable. Your only option is to get a surgery (Scenario 4) by a human surgical team, (Scenario 5) by a human surgical team supported by AI, or (Scenario 6) by an autonomous AI. In case of complications, the hospital is liable.

2.9.2 A-2: Questionnaire

1 – Intention to use: (1) I would definitely use the described surgical opportunity if it would be available; (2) I intend to use the described surgical opportunity if it would be available; (3) I plan to use the described surgical opportunity if it would be available.
2 – Attitude (HIS): The described surgical opportunity would be… (1) … advantageous; (2) … satisfactory; (3) … important; (4) … enjoyable; (5) I would like the use of the described surgical opportunity.
3 – Fear (HIS): The described surgical opportunity makes me… (1) … feel anxious, uncomfortable, as it could hurt me; (2) … feel anxious, very strained, as I am in danger; (3) … feel anxious, shaky and nervous.
4 – Perceived HIS Efficacy: (1) After using the described surgical opportunity, I think that my sufferings will be reduced; (2) Due to the described surgical opportunity, my sufferings will be reduced; (3) I am convinced that the described surgical opportunity will reduce my sufferings.
5 – Perceived self-efficacy: (1) I am confident that the described surgical opportunity will reduce my sufferings; (2) Whether I undergo surgery or not is solely dependent on myself; (3) If I really want to, I can undergo surgery at any time; (4) Whether I undergo surgery or not, is solely up to me.
6 – Attitude (Disease): Having the described disease would be… (1) … not advantageous; (2) … not satisfactory; (3) … not important; (4) … not enjoyable; (5) I would not like having the described disease.
7 – Fear (Disease): Having the described disease lets me… (1) … feel anxious, uncomfortable, as it could hurt me; (2) … feel anxious, very strained, as I am in danger; (3) … feel anxious, shaky and nervous.

8 – Perceived susceptibility: (1) It is very likely that I fall ill with the disease; (2) My chances to fall ill with the disease are high; (3) I am someone who very likely has to undergo surgery with the disease; (4) The probability that I fall ill with the disease is much higher than within my peer group.
9 – Perceived severity: (1) When I fall ill with the disease, it is very painful; (2) The disease would cause me major difficulties; (3) When I fall ill with the disease, I get seriously ill; (4) The disease will make me depressive and anxious; (5) The disease will make me dependent from others to master the daily life; (6) When I fall ill with the disease, I must bear severe pain; (7) The disease will let my family suffer severely.
10 – Maladaptive rewards: (1) The waiving of the described surgical opportunity will save me a lot of time; (2) The waiving of the described surgical opportunity will spare me pains; (3) The described surgical opportunity would limit my mobility.
11 – Perceived norms: (1) Individuals from whom I let myself be influenced would advise me to use the described surgical opportunity; (2) Individuals who are important to me would advise me to use the described surgical opportunity; (3) Individuals whose opinion I appreciate would advise me to use the described surgical opportunity; (4) Individuals in a situation comparable to myself would advise me to use the described surgical opportunity.
12 – Computer skills: How would you evaluate your general computer skills?
13 – Technical knowledge AI: How would you evaluate your technical knowledge of artificial intelligence?
14 – Experience with AI: How would you evaluate your experience with artificial intelligence-based service?

3 The Threat of New Health Information Systems for Established Services[6]

Tanja Sophie Gesk, Johannes Wichmann and Michael Leyer

Abstract

Ongoing digitalization is leading to new health information systems (HIS) that help patients to better manage their health activities. For this, we use an integrated model following a duality approach to explain how patients intend to use HIS in order to change their ongoing service usage. On the one hand, we consider maladaptive appraisals by investigating routines that patients have already developed concerning their specific disease. On the other hand, we take adaptive appraisals into account that examine perceptions in routine-changing due to the new HIS. The results extend prior insights on HIS usage intentions for one-point-in-time to ongoing services.

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3.1 Introduction

The ongoing digitalization is leading to new health information systems (HIS) and related health services, as technologies are associated with changes of processes also allowing new service offers (Longoni et al., 2019; Martinez, 2019). With new health services, patients are particularly affected as they have to adapt their disease-related behaviour when being involved in the co-creation of such ongoing health services (Bahadori et al., 2020; Yi & Gong, 2013). In order to analyse the intention to use of new HIS, Gesk et al. (2021) developed an integrated framework bringing various theories together that allows to better understand the back and forth between disease and new solution. The duality approach of the model considers on the one side maladaptive appraisals referring to disease-related behaviour and on the other side adaptive appraisals as perceptions in routine-changing due to a new HIS (Gesk et al., 2021).

Gesk et al. (2021) applied the integrated model on artificial intelligence (AI)-based HIS regarding surgeries as a prominent health service. Especially HIS that are AI-based have a high potential to increase the quality of services (Zheng et al., 2021). AI can adapt to changing situations as its algorithms are capable of changing due to self-learning. Thus, service qualities in healthcare can be improved by using AI-based HIS (Loftus et al., 2020; Zhou et al., 2020). The results of the prior study however focus on one-point-in-time interventions, leaving out an understanding regarding the intention to use AI-based HIS in ongoing services (Gesk et al., 2021). The study results show that the intention to use is mainly explained by the adaptive appraisals while maladaptive appraisals are not relevant in this regard (Gesk et al., 2021). Hence, the research question remains open whether a similar effect can be observed for ongoing services.

In order to answer the research question, we applied the integrated framework to the disease “diabetes” that is particularly suitable to investigate ongoing healthcare services that are present in the daily lives of individuals with diabetes (Leyer & Iloska, 2021). In this regard, we investigated the balance of whether diabetes patients stick to their existing disease-related routine or intend to use the new HIS in order to regular their blood sugar better.

3.2 Conceptual Background

Health care services support patients by handling their daily lives concerning their disease related behaviour. There are different types of services (Ballegaard et al., 2008). Technical healthcare services are called HIS (Gesk et al., 2021). This HIS can be based on different types of technologies. The most potential technology for healthcare services are AI-based HIS (Loftus et al., 2020; Zhou et al., 2020). Characteristics of AI are the abilities that require intelligence. These include the abilities of problem-solving, shot-following, perception, and communication (Leyer & Schneider, 2019; Russel & Norvig, 2010; Rzepka & Berger, 2018). Furthermore, AI-based HIS are different from other HIS because the AI-based software is able to perform self-learning (Zhou et al., 2020).

In addition, we focus our study on the lifelong disease of diabetes. There are already HIS that support and help diabetes patients with concerns regarding diabetes. New HIS can serve a better service for diabetes patients (Leyer & Iloska, 2021). The integrated theoretical model is used for diabetes scenarios with three different types of services. Especially, new AI-based HIS have been proven to be effective in healthcare (Gesk et al., 2021; Zheng et al., 2021). This capacity can be used to define individual intervention plans considering diabetes issues (Leyer & Iloska, 2021).

3.3 Theoretical Background

The integrated model of Gesk et al. (2021) combines health sciences, information systems, and psychology theories to investigate the intention to use new HIS. Thereby, the intention to use new HIS is mainly determined by the duality approach. In healthcare settings, investigations handling disease-related behaviour and new intentions concerning a specific behaviour are performed by balancing adaptive and maladaptive appraisals (called duality approach (Witte, 1994)).

On the one hand, the focus is on the disease-related routine, which is a specific behaviour patients perform, since they are already familiar with their ongoing disease and know what to do and when to do it to be well. Patients stick to a disease-related routine even if this might result in disadvantages while having the benefits to stay with a familiar routine.

On the other hand, a new HIS also promises advantages in handling the disease but is associated with adoption costs (Floyd et al., 2000) or fear of the unknown (Rogers, 1975; Venkatesh et al., 2012), which might influence a disease-related routine. Both behaviour streams are balanced by the individual considering their advantages and disadvantages to ultimately determine whether she/he intends to use HIS. Figure 6 provides an overview about the integrated theoretical model.

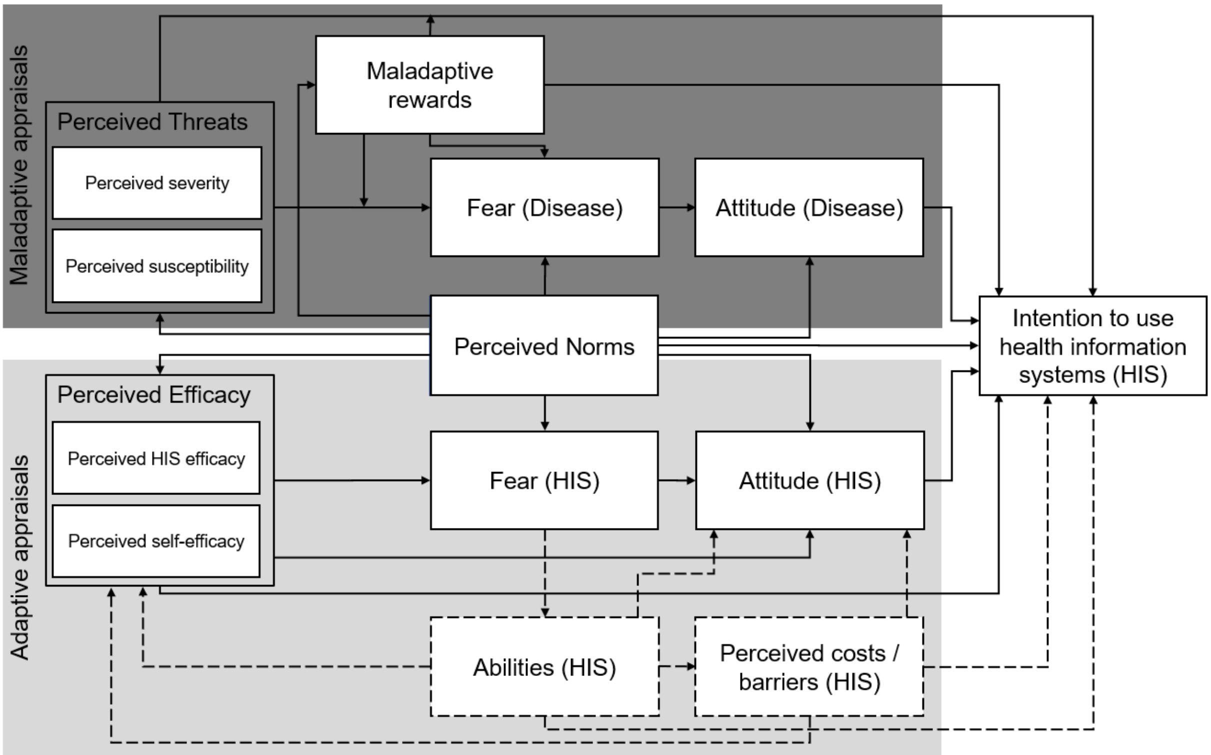

Figure 6: Integrated theoretical model according to Gesk et al. (2021)

3.4 Methodology

Based on the integrated theoretical model of Gesk et al. (2021) we deducted specific hypotheses. On the one hand, the hypotheses addressed the disease-related behaviour of patients and on the other hand, we estimate perceptions that influence the disease-related behaviour by using new HIS (Gesk et al., 2021; Murtagh et al., 2012). Regarding the utilized AI-based health services, we decided that "perceived costs/barriers (HIS)" are not useful because the probands cannot assess the monetary and non-monetary costs of the use of such a service.

As the new HIS for diabetes is not available yet and our findings are based on a description of the AI-based diabetes HIS, we used a scenario-based research design that includes manipulations and the individual decision of the probands (Webster & Trevino, 1995). We did so, as we wanted to investigate changes in behaviour, if the patients are treated by the diabetologist only (Scenario 1); the diabetologist with AI-support (Scenario 2); and the AI only (Scenario 3).

We designed questionnaires to assess the scenarios by using the template of Gesk et al. (2021) which includes the following reflective variables: intention to use (3 items), attitude (HIS) (5 items), perceived norms (4 items), perceived behavioural control (4 items), and attitude (disease) (5 items), perceived response efficacy (3 items) and fear regarding HIS and disease (3 items). We also used the formative variables perceived vulnerability (4 items), perceived severity (7 items) as well as maladaptive rewards (3 items). Further, we asked our participants to assess themselves concerning experience with AI-based services, general computer skills, and technical knowledge about AI by using a Five-point Likert scale. For gathering empirical data, we use the crowd working platform Clickworker, which is similar to Amazon MTurk. For our study, we chose participants between 18 and 70 years that are suffering from diabetes type 1. We got a total number of 197 participants, which are divided among the scenarios as follows: Scenario 1: 67; Scenario 2: 60; Scenario 3: 70.

We used Partial Least Square (PLS) methods to examine the applied integrated theoretical model. We performed bootstrapping with 5,000 subsamples in SmartPLS 3.3.3 (Hair et al., 2011). The analysis of Hair et al. (2011) concerning the reflective and formative measurement models was carried out. First, all reflective variables fulfilled the indicator reliability criteria as the values were above the threshold of 0.7. The composite reliability was also confirmed as the values were above 0.7 and the extracted mean variance was above 0.5 (Hair et al., 2011). There was also discriminant validity according to the heterotrait-monotrait method, as scores were below 0.9 (Henseler, Ringle, et al., 2014).

Second, the formative variables were tested. Multicollinearity was given as the variance inflation factors were below 5 (Hair et al., 2011). The relative and absolute importance of the indicators were examined by examining and confirming the importance of the weights and loads.

Third, the quality of the structural model was investigated by adapting the model using the standardized square mean value (Henseler et al., 2016). The values for the saturated and estimated SRMR are below 0.1. In addition, the blindfolding with a distance of 7 resulted in a positive Stone-Geisser Q^2. The model thus proves to be relevant for the course of the endogenous variables (Henseler et al., 2016).

3.5 Findings

The mean values of the respective service intentions are as follows: Scenario 1: diabetologist: 3.92 (R^2: .6); Scenario 2: diabetologist with AI-support: 3.87 (R^2: .62); Scenario 3: AI only: 3.98 (R^2: .69). This shows that all three options are similarly attractive. We then use the model to calculate the results for the hypotheses for each scenario. Figure 7 provides an overview that only highlights the variables with significant path coefficients.

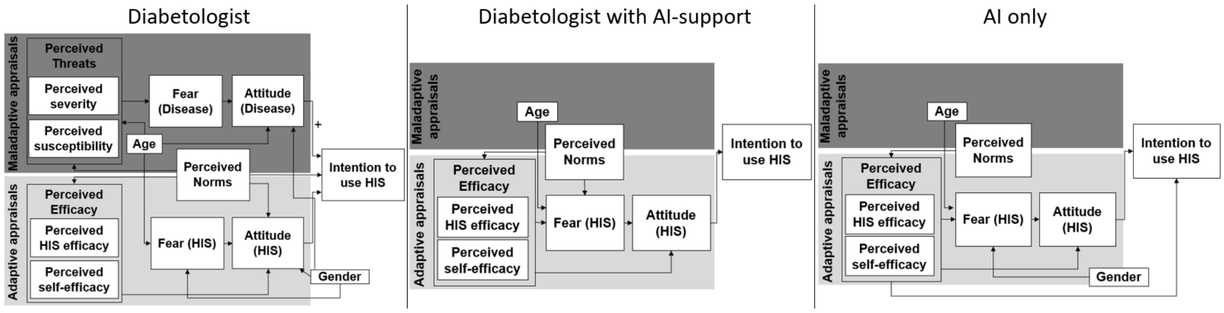

Figure 7: Results regarding hypotheses according to scenarios

3.6 Discussion

By comparing the results of the three different scenarios of our study, we examined certain differences in variables which explain the intention to use the new HIS for ongoing service usage. First, as scenario 1 represents the current treatment for diabetes, adaptive and maladaptive appraisals influence the intention to use the new HIS. We thereby support Gesk et al. (2021)'s proposition in that the current disease-related behaviour and perceptions about changing the behaviour influence the intention to use new HIS in ongoing services, as well as for one-point-in-time services. Further, we support Gesk et al. (2021)'s perception that, if the new HIS comes into play, the disease-related behaviour is no longer relevant for predicting the intention to use new HIS on an ongoing basis, as for one-point-in-time. Similar to the study of Gesk et al. (2021), our results reflect that the evaluations of the new HIS (as adaptive appraisals) are the only relevant explanatory strand of our duality approach in predicting the intention to use new HIS.

Usage intentions of ongoing health services performed by humans with new HIS are formed only by the reference object of HIS. Here, only the attitude towards this new HIS carries a significant influence on intention to use. However, for health services with a short time-spawn that are also performed by humans with new HIS, both reference objects are influential in forming the intention to use (compared to scenario 2 and 5 in Gesk et al., 2021).

Intentions to use ongoing health services performed only by HIS are formed by attitudes regarding HIS as well as the perceived efficacy of HIS. This means that in this case also only the reference object HIS contributes to the formation of the intention to use. The same result can be seen with Gesk, where only the attitude towards HIS contributes to the formation (regarding scenario 3 and 4 in Gesk et al., 2021).

In addition, it is important to recognize that fear of HIS is an important influencing factor when it comes to forming the intention to use new health services. Thus, this influence can be seen regardless of whether the service is short-term or ongoing and what type of service it is (compared with Gesk et al., 2021).

3.7 Academic Implications

The theoretical implications of our study are that the integrated theoretical model can be applied not only to one-point-in-time situations but also to assess new HIS in ongoing services. Our results confirm however the trend that the intention to use of more abstract HIS service offers is mainly determined by the adaptive appraisals. Moreover, the empirical results show that the integrated model is also feasible for individuals affected by a disease and not hypothetical affected individuals as included in Gesk et al. (2021). The usage of the model helps to understand how the usage intention of new HIS is formed by better modelling the reasons for balancing adaptive and maladaptive appraisals.

3.8 Practical Implications

The intention to use is at a similar level for all three HIS offered as an ongoing diabetes service. Therefore, it appears useful for developers and health-oriented companies to continue investing in innovative AI-based diabetes HIS or continuing to drive development. Our results can be helpful for health-related organisations to develop such HIS better and to facilitate the implementation of new HIS in ongoing services. For this purpose, employees must be sufficiently familiarized with the new HIS and trained. By transparently explaining the efficacy to individuals with diabetes, fear regarding HIS can be reduced simultaneously and thus is a promising way to help individuals with diabetes in their daily life.

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4 The Disease or the Vaccination: What is More Important when Deciding Whether to Vaccinate?[7]

Tanja Sophie Gesk, Johannes Wichmann and Michael Leyer

Abstract

Rationale: Vaccinations provide adequate protection against many virus-related diseases. Nonetheless, many individuals refuse voluntary vaccinations, and their refusal could contribute to the spread of diseases. Previous research on the intention to vaccinate has been limited by focusing on a single target group.

Objective: In this study, we develop an integrated theoretical framework incorporating the dual approach with relevant theories related to both disease and vaccination. Our objective is to examine the behavioral reasons for the decision to vaccinate or not. The vaccination-related appraisals concern aspects of vaccination and the disease-related appraisals concern aspects of COVID-19. The framework is applied to the much-discussed context of COVID-19 vaccination.

Method: We investigate the intention to vaccinate of two target groups, unvaccinated individuals and twice-vaccinated individuals, with a partial squares structured equation model.

Results: Our results show that unvaccinated individuals are driven in their intention to vaccinate by their attitude (toward vaccination); factors relating to the disease have no influence. In contrast, when deciding whether to be revaccinated, twice-vaccinated individuals balance factors relating to vaccination and factors relating to disease.

Conclusions: We conclude that the proposed integrated theoretical model is appropriate for investigating diverse target groups and deriving implications.

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[7] The article is currently under review for publication in Social Science and Medicine journal.

4.1 Introduction

For many virus-related diseases, vaccination is efficient to prevent severe illness and death (e.g., Ling et al., 2019). Some diseases, such as poliomyelitis, have been (temporarily) eradicated by vaccination (Dubé et al., 2013). Vaccinations for certain diseases, such as smallpox, are compulsory in many countries. In particular, many childhood vaccinations are mandated in order to protect children from diseases that can lead to long-term illness or even death (Jedwab et al., 2021). Vaccinations against other diseases are voluntary (Fall et al., 2018). Since an increase in the rate of voluntary vaccinations requires decisions on the part of adults, it is important to understand which factors drive decision-making regarding vaccination. Because some vaccinations require revaccination (boosters) after some time (e.g., COVID-19 vaccination, Sasaki et al., 2022; e.g., tetanus vaccination; Simonsen et al., 1984), individuals may also have to decide for or against revaccination.

Several studies have investigated decisions and intentions regarding vaccinations, such as Fall et al. (2018), Guidry et al. (2021), and Shiloh et al. (2021). For example, Marra et al. (2016) investigated decision-making for human papillomavirus (HPV) vaccinations. Their studies examined the intention to vaccinate without considering the number of vaccinations and the current vaccination status of the participants. As a result, it remains unknown whether unvaccinated and already vaccinated individuals have the same decision-making process regarding (re)vaccination, a matter that requires clarification for purposes of target-oriented communication and to take account of the fact that behavioral reasoning for getting vaccinated may change over time, causing vaccination campaigns to falter, especially for new vaccines (EuropeanCommission, 2022; Mathieu et al., 2021). Addressing this research gap will also help governments to increase vaccination preparedness and to manage crises, such as pandemics, more effectively. It is therefore important to understand which psychological factors distinguish unvaccinated and twice-vaccinated individuals in terms of intention to vaccinate. Moreover, it is important to consider both individuals who have a) not previously chosen to get vaccinated and b) previously twice chosen to get vaccinated but are now facing the decision to revaccinate for the third time. The same questions are relevant to other vaccinations, such as tetanus (Simonsen et al., 1984), for which (albeit after a longer period) a booster is also required.

To address this gap, we develop an integrated theoretical framework built on healthcare and cognitive psychology theories with a duality approach at its core. By integrating these theories, we can understand the individual's intention to engage in health-related behaviors, which depends on the assessment of the disease in question and actions taken to address the disease

(Chu & Liu, 2021). We apply this framework to the context of COVID-19 to consider psychological factors from two perspectives: that of disease and that of vaccination. Both perspectives are essential for understanding how individuals reach a decision for or against a (re)vaccination (Chu & Liu, 2021).

We gathered data from Germany in December 2021. Simultaneously, there was (as there still is today) considerable resistance among a large group of citizens (with 28% of the population not vaccinated), and booster vaccinations had just become generally available (RKI, 2021; Statista, 2022). Our results thus contribute to a better theoretical understanding of whether and how individuals balance disease and vaccination in determining the intention to get (re)vaccinated. On a practical level, our results provide guidance for governmental institutions, organizations, and society on how to promote vaccinations for specific target groups, namely twice-vaccinated individuals facing the decision to revaccinate, and unvaccinated individuals facing the decision to vaccinate for the first time.

This article is organized as follows. First, we review the theoretical work on influencing factors in the context of vaccinations, explain our choice of theory, and develop our hypotheses. Then, we describe our materials and methods, presenting our questionnaire, sample, and data analysis. Next, we offer our findings, including descriptive statistics and results of hypotheses testing. After discussing those findings, we conclude with theoretical and practical implications, limitations of the study, and directions for future research.

4.2 Theoretical Background

4.2.1 Studies on Understanding Vaccination Decisions

Of the many studies on the intention to vaccinate, a considerable number focus on vaccination against (seasonal) influenza, COVID-19, and HPV, and several cognitive theories have been applied.

A commonly used model, the health belief model (HBM), investigates the acceptance of health prevention measures (Rosenstock, 1974a). HBM focuses on perceived threats and behavioral evaluation of preventive actions as the two drivers of intention to engage in healthy behavior For example, Hsu et al. (2009) used HBM to investigate women's willingness to be vaccinated against HPV. They found that educational campaigns should focus on vaccination's efficacy, safety, and benefits. In addition, education about HPV infection should be provided by (Hsu et al., 2009).

Other studies have used protection motivation theory (PMT), a development of HBM that adds further variables, including response efficacy, self-efficacy, and intrinsic and extrinsic rewards, as antecedents of risk assessment (Floyd et al., 2000). Davis et al. (2021) show that a direct comparison of efficacies between COVID-19 and influenza vaccination increase the intention to vaccinate against COVID-19. Eberhardt and Ling (2021) compare the willingness to vaccinate unvaccinated and vaccinated individuals. In addition, the study shows that COVID-19 conspiracy theories have a strong influence on the intention to vaccinate. Therefore, communication campaigns should focus on the perceived severity of and vulnerability to COVID-19, the efficacy of vaccination, the minimization of benefits of non-vaccination, and countering conspiracy theories (Eberhardt & Ling, 2021). Li et al. (2021) also demonstrate through PMT that the safety, efficacy, and accessibility of the COVID-19 vaccine will increase the intention to vaccinate. Ling et al. (2019) illustrate that all PMT constructs significantly impact the intention to vaccinate against influenza.

Ajzen (1991)'s theory of planned behavior (TPB) has also been widely used to measure the intention to vaccinate. TPB assumes that individual behavior is controlled by behavioral intentions and is influenced by individual attitudes toward behavior, subjective norms, and perceived behavioral control (Ajzen, 1991). Fernandes et al. (2021) show in their study how the willingness to vaccinate against COVID-19 among Portuguese people for themselves and their children. In particular, general beliefs and attitudes about the COVID-19 vaccine are highly influential in using the TPB (Fernandes et al., 2021).

Furthermore, there are studies that combine serval theories. Shmueli (2021) likewise applies the combination of HBM and TPB to investigate vaccination readiness against COVID-19 in Israel. The results show that seasonal influenza vaccination behavior, perceived efficacy, perceived severity of COVID-19, perceived norms and perceived behavioral control impact the intention to vaccinate (Shmueli, 2021). Guidry et al. (2021) investigate due HBM and TPB the intention to vaccinate against COVID-19 compared to the opportunity to get vaccinated when vaccines were given emergency approval. Thus, perceived norms, attitude (toward vaccination), perceived efficacy, mistrust, and perceived threat toward disease impact intention to vaccinate. Further, a correction of misinformation should go beyond communication campaigns to restore trust in government institutions (Guidry et al., 2021).

Fall et al. (2018) use HBM and self-determination theory to predict the intention to vaccinate against influenza among university students in France. Autonomous motivation and self-efficacy influence the intention to vaccinate (Fall et al., 2018). Marra et al. (2016) use HBM and social cognition model to investigate the intention to vaccinate against HPV among male patients at a clinic in Amsterdam. The intention to vaccinate against HPV among men who have sex with women (in comparison with men who have sex with men) is influenced by subjective norms, self-efficacy, and knowledge of HPV. Further, the intention to vaccinate decreases when individuals have to pay for vaccination (Marra et al., 2016). Shiloh et al. (2021) use HBM, PMT, and the self-regulation model to predict the intention and behavior in relation getting vaccinated against COVID-19. The regret for having declined vaccination, past influenza vaccination, perceived social norms, attitude (toward vaccination), trust in vaccination, vaccination barriers, and COVID-19 representations impact the vaccination behavior. Further, information-gathering activities could influence the intention–behavior gap (Shiloh et al., 2021).

Some studies have also used the extended parallel processing model (EPPM; Witte, 1994) to distinguish between aspects of behavior that concern disease and aspects that concern vaccination. Chu and Liu (2021) use HBM, TPB, and EPPM to investigate the intention to vaccinate against different diseases. According to Chu and Liu (2021), severity, fear towards COVID-19 disease, and perceived efficacy impact the intention to vaccinate. In contrast, safety concerns negatively influence the intention to vaccinate (Chu & Liu, 2021).

Summing up these prior studies, it becomes evident that they share common elements but have their specific foci. Using one of the single models would exclude the holistic view on variables identified in the different models. Hence, a model is missing that combines the different aspects to allow for a consideration of all variables identified.

4.2.2 Integrated Theoretical Framework

The basis of our integrated theoretical framework is the duality approach of vaccination-related and disease-related appraisals (see Witte, 1994). This means that an individual must decide whether to accept a particular treatment and/or engage in health-promoting behaviors (called vaccination-related appraisals), or to reject a treatment and engage in behaviors that are not health-promoting (called disease-related appraisals) (Gücin & Berk, 2015). Individuals are balancing between vaccination-related and disease-related appraisals in their decision-making (Gesk et al., 2021). Thus, the individual has to consider whether to seek medical treatment to alleviate or cure their condition (Gesk et al., 2021). The duality approach has been applied to the context of vaccines by Chu and Liu (2021). The vaccination-related appraisals concern with aspects of vaccination, whereas disease-related appraisals concern aspects of COVID-19. Thus, the individual has to balance between these appraisals during vaccine decision-making. In contrast to Chu and Liu (2021) and Witte (1994), however, our integrated theoretical framework focuses on processing specific health-related messages instead of on general behavior toward health-related topics. Therefore, within the duality approach we use EPPM, which investigates perceived efficacy, perceived threat, and fear. According to EPPM, vaccination-related behavior is more cognitive, whereas disease-related behavior is more emotional (Witte, 1994).

Fear is an important predictor in many decision-making processes (Lawrence et al., 2022). Therefore, we draw on PMT, which introduces the construct of fear operating as a mediator between risk assessment and behavior and groups' social influences, on the one hand, and between individual differences and general influencing factors, on the other (Izard et al., 1993).

We exploit the three lines of argumentation of the reasoned action approach (RAA) to behavior, which is a development of TPB (Fishbein & Ajzen, 2010). Furthermore, we integrate into our framework relevant theories from psychology and healthcare, namely PMT (Floyd et al., 2000; Rogers, 1975), EPPM (Witte, 1994) and RAA (Fishbein & Ajzen, 2010).

The perceived threat, which includes perceived vulnerability and perceived severity, is essential for the intention to vaccinate (e.g., Davis et al., 2021; Ling et al., 2019); that intention increases when individuals feel threatened by the disease (Fall et al., 2018; Hsu et al., 2009). Hence, our first hypothesis is as follows:

> *H1: Perceived threats have (a) a positive influence on fear (of disease) and (b) a positive influence on intention to vaccinate.*

The benefits of not getting vaccinated are called disease-related rewards (Ling et al., 2019) and include perceived costs associated with vaccination. Individuals who are not vaccinated do not have the expense that vaccination entails and thus receive disease-related rewards for not getting vaccinated (Ling et al., 2019). According to Ling et al. (2019), disease-related rewards are essential for the intention to vaccinate. On the one hand, that intention may be increased if the benefits of receiving vaccination outweigh the benefits of non-vaccination. On the other, the benefits of not getting vaccinated may outweigh the benefits of receiving the vaccination. Particularly in the case of vaccines that are new or have been developed rapidly, some individuals may want to wait until improved versions are available (Callaghan et al., 2021; Thunström et al., 2021). Although fear (of disease) increases, intention to vaccinate decreases (Gesk et al., 2021). Hence, disease-related rewards and fear (of disease) could negatively influence the intention to vaccinate. This leads to our second hypothesis:

H2: Disease-related rewards have (a) a negative influence on fear (of disease) and (b) a negative influence on intention to vaccinate.

Fear is a negative emotion that influences intention toward a behavior (Brehm, 1966). In the context of vaccination, fear is known to increase attitude (toward disease) (Liu et al., 2021), which leads to our third hypothesis:

H3: Fear (of disease) positively influences attitude (toward disease).

Attitude (toward disease) reflects an individual's opinions about the disease and has the most significant influence on intention (Brehm, 1966; Fishbein & Ajzen, 2010; Gust et al., 2004). Accordingly, our fourth hypothesis is as follows:

H4: Attitude (toward disease) positively influences intention to vaccinate.

As soon as unknown reference objects are added, the focus switches to them. Unknown reference objects include new technology, such as artificial intelligence (Gesk et al., 2021), and new vaccination methods, such as those used against COVID-19 (Mathieu et al., 2021). Perceived efficacy is determined by perceived behavioral control and perceived efficacy of vaccination (Davis et al., 2021). Perceived efficacy depends on vaccination campaigns and reputable sources of information that raise awareness and educate people about specific vaccines, which has a positive influence on attitude (toward vaccination) and intention to vaccinate (Lazarus et al., 2021). Fear (of vaccinations) can have different triggers, such as fear of needles. However, the perceived efficacy of vaccination may minimize fear (Dubé et al., 2013). Therefore, our fifth hypothesis is as follows:

H5: Perceived efficacy has a negative influence on (a) fear (of vaccination) and a positive influence on (b) attitude (toward vaccination) and on (c) intention to vaccinate.

By addressing fear as an emotion, previous studies have shown that fear (of vaccination) negatively influences the intention to vaccinate (e.g., Guidry et al., 2021). Information overload could cause fear and lead to negative attitudes toward vaccine (Honora et al., 2022). One example is AstraZeneca's AZD1222 (ChAdOx1) vaccine against COVID-19, which is associated with a small risk of blood clots (Fernandes et al., 2021). When the association became known, the intention to vaccinate using the AstraZeneca vaccine decreased (Fernandes et al., 2021). Misinformation also increases fear (of vaccinations) and has a negative effect on attitude (toward vaccination) and intention to vaccinate (Fernandes et al., 2021). Accordingly, our sixth hypothesis is as follows:

H6: Fear (of vaccination) negatively influences attitude (toward vaccination).

Fernandes et al. (2021) determined that a positive attitude (toward vaccination) increases the intention to vaccinate. Hence, our seventh hypothesis is as follows:

H7: Attitude (toward vaccination) positively influences intention to vaccinate.

Perceived norms are disease-related or vaccination-related appraisals, but are also important factors influencing the intention to vaccinate. Specifically, if health communication regarding COVID-19 vaccinations is inadequate, the public's perception of the efficacy of vaccination declines, leading in some cases to vaccination refusal (Shmueli, 2021). Perceived norms represent the opinions of others who are important to the individuals in question about the disease and associated vaccinations (Chu & Liu, 2021; Guidry et al., 2021). Accordingly, our final hypothesis is as follows:

H8: Perceived norms have a positive influence on (a) perceived threats, (b) fear (of disease), (d) intention to vaccinate, (e) attitude (toward vaccination), and (g) perceived efficacy, and a negative influence on (c) attitude (toward disease), (f) fear (of vaccination), and (h) disease-related rewards.

Figure 8 provides an overview.

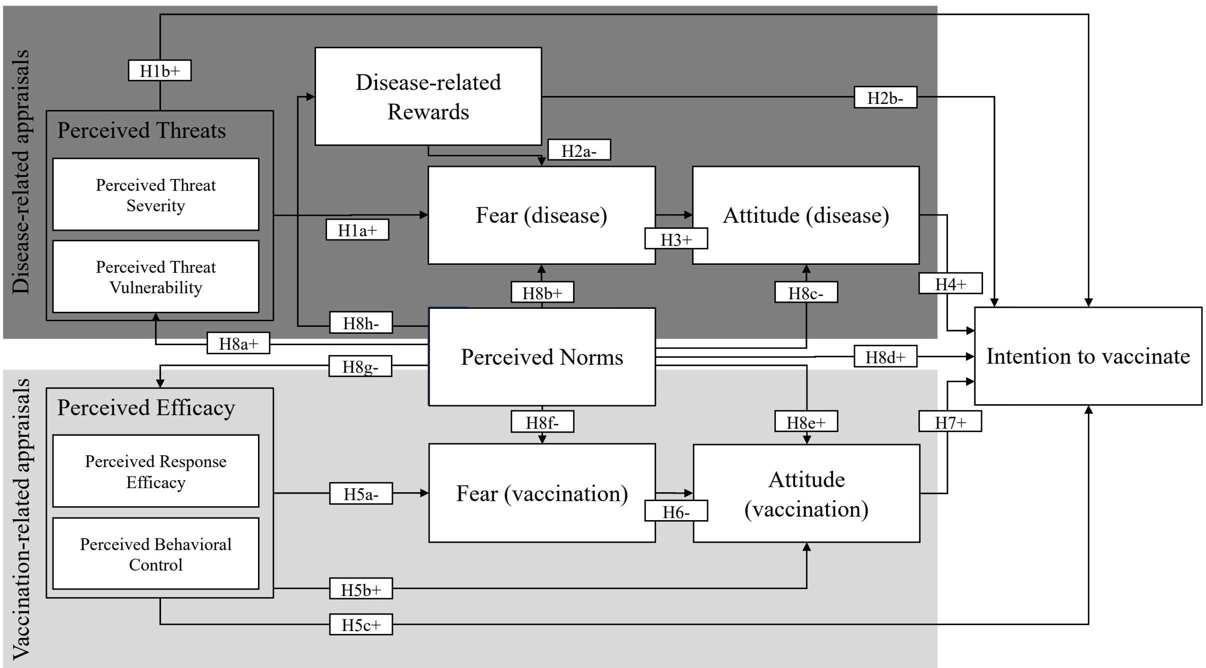

Figure 8: Integrated theoretical framework and hypotheses

4.3 Materials and Methods

4.3.1 Questionnaire

To understand which factors are more important in the decision for or against vaccination, we conducted a survey in December 2021 in Germany. At that time, 28% of German citizens were not vaccinated, and 70% were twice-vaccinated. As there was a range of mRNA vaccines available, we did not limit our study to a specific COVID-19 vaccine (RKI, 2021; Statista, 2022).

First, we collected information about the vaccination status of our participants. For our investigation, we needed unvaccinated and twice-vaccinated probands without booster vaccination. Therefore, the booster status was an exclusion criterion for our study. Further, we selected control variables in line with recommendations of Goodman et al. (2012) on attention checks. In line with the integrated theoretical framework, we adapted the reflective and formative variables in the way our related work. Therefore, we used the item template from Fishbein and Ajzen (2010) for intention to use (three items), attitude (toward vaccination) (five items), perceived norms (four items), perceived behavioral control (three items), and attitude (toward disease) (five items). Fishbein and Ajzen (2010) have a much tested sample questionnaire which conducts to RAA. For reflective variables fear (of vaccination) (three items) and fear (of disease) (three items), we used the item template of Izard et al. (1993) and for perceived response efficacy (three items), we used items of Taheri-Kharameh et al. (2020) and Park (2011). Izard et al. (1993) discuss the role of emotions and state that fear alters the way we perceive and think. For formative variables of perceived severity (seven items), perceived threat vulnerability (four items), and disease-related rewards (three items), we adapted the item templates of Boss et al. (2015) and Taheri-Kharameh et al. (2020). Boss et al. (2015) and Taheri-Kharameh et al. (2020) deal with perceptions of new unknown technologies and situations. We also adapted COVID-19-related adjustments from Chu and Liu (2021), Li et al. (2021), and Mercadante and Law (2021). All items were measured on a seven-point Likert scale ranging from "1 – Do not agree at all" to "7 - Fully agree" and no scale was reversed (e.g. attitude regarding the disease was also positively rated, but we used the negative form of the attributes). In addition, we collected basic demographic data (age, gender, and level of education). The questionnaire is shown in the appendix.

4.3.2 Sample

A total of 290 individuals participated in the survey, of whom 36 were excluded because they stated that they had already received their booster vaccination. Of the 254 participants, 82 stated that they were not vaccinated against COVID-19, and 172 stated that they were twice-vaccinated but had not yet received a booster vaccination. Thus, we evaluated data from the remaining 254 participants of whom 39.0 percent (n = 99) were female, and 60.2 percent (n = 153) were male. Additionally, 0.8 percent (n = 2) of our participants preferred not to indicate their gender. The mean age of our individuals was 38.43 years (SD = 12.00; minimum = 19, maximum = 74). The groups were similar in age profile, with an average age of 37.83 years (SD = 10.85) for the unvaccinated and an average of 38.72 years (SD = 12.53) for the twice-vaccinated. To classify the educational levels of our participants, we applied the ISCED 2011 categories (UNESCO-UIS, 2012), according to which 1.2% (n = 3) of our participants had attained the highest level (level 8; doctoral degree or equivalent) and 1.6% (n = 4) had attained level 2 (lower secondary school leaving qualifications). The most frequently attained level (24.4%, n = 62) was level 3 (upper secondary education), which indicates that these individuals did not attend university. We used the crowdsourcing platform Clickworker (which is like Amazon MTurk) to gather our data, and we paid individuals for participating in the survey, following the recommendations of Goodman et al. (2012) to ensure the validity of the data.

4.3.3 Data analysis

We used partial least squares to analyze our data, a method that is particularly suitable for processing structural equation models with a mixture of formative, reflective, and second-order constructs (Hair et al., 2019). As we consider two groups, unvaccinated and twice-vaccinated individuals, we follow recommendations of Hair et al. (2021) concerning multigroup analysis in PLS-SEM. For this, we conducted a Bootstrapping procedure and permutation tests with 5,000 resamples in SmartPLS 4.0.8.7. Following the procedure described by Hair et al. (2019), we analyzed reflective and formative measurement models first and second, before examining our structural model as the third step.

First, all reflective variables met indicator reliability criteria, as the loadings were above 0.7 (see appendix). Composite reliability was confirmed, as values were above 0.7 and the average variance extracted was higher than 0.5 (see appendix; Hair et al., 2019). Discriminant validity using the heterotrait–monotrait was also confirmed, as scores were less than 0.9 (see appendix; Henseler, Dijkstra, et al., 2014).

Second, formative variables were tested. The convergent validity was given because the outer weights and outer loadings were above 0.7 (see appendix). Multicollinearity was found not to be an issue, as the variance inflation factors (VIF) were below 5 (Hair et al., 2019). The relative and absolute importance of indicators were examined by testing and confirming the significance of weights and loadings (see appendix).

Third, the structural model was checked for model fit using the standardized root mean square residual (Henseler et al., 2016). The values for the saturated SRMR (0.093) were less than the required 0.1. The collinearity (VIF) was also given because the values were above 5 (see appendix, Hair et al., 2019). We investigated effect sizes using f^2-values according to Cohen (1988). While Cohen (1988) proposed to use effect sizes of 0.02, 0.15, and 0.35 for small, medium, and large effects, we performed statistical power analyses according to Kock and Hadaya (2018) using G*Power 3.1.9.7 (Mayr et al., 2007) and adapted the threshold for small effect sizes due to our sample sizes. Thus, for small effect sizes, the threshold for unvaccinated is f^2=0.08 and for unvaccinated is f^2=0.04. According to Hair et al. (2019), R^2 for the unvaccinated (R^2=.506) and for the twice-vaccinated (R^2=.722) were considered as moderate. Due to check for measurement model invariance and to determine whether our group significances are meaningful, we followed MICOM procedure according to Hair et al. (2021). By conducting all required steps, we determined that the results of the following variables are considered meaningful for both groups: attitude (disease), attitude (vaccination), fear (disease), fear (vaccination), perceived threats, perceived behavioral control, perceived severity, and perceived threat vulnerability. As a final step for our statistical tests, we performed PLS predictions for the unvaccinated and the twice-vaccinated according to Shmueli et al. (2019). Our PLS-SEM Q^2 prediction values were exclusively positive, and the prediction errors were not highly symmetrically distributed. Therefore, we tested whether our PLS-SEM mean absolute errors (MAEs) were higher than those of the linear regression model (LM). Since the majority of our PLS MAEs were higher than the LM errors (see appendix), we found medium predictive power in our model for both, the unvaccinated and the twice-vaccinated, according to Shmueli et al. (2019). All in all, the model is relevant for the course of endogenous variables (Henseler et al., 2016).

4.4 Results

4.4.1 Descriptive statistics

The descriptive statistics for unvaccinated participants are presented in Table 4.

	Mean	SD	1	2	3	4	5	6	7	8	9
1: Perceived norms	3.77	1.63	1.000	.329	.372	.269	.179	-.026	.173	-.062	.109
2: Intention	2.59	1.31		1.000	.677	.242	.175	-.207	.307	-.188	.350

3: Attitude (vaccination)	2.98	1.54			1.000	.458	.212	-.142	.388	-.269	.437
4: Perceived efficacy	4.22	1.29				1.000	.360	-.044	.347	-.260	.312
5: Attitude (disease)	5.51	1.41					1.000	.205	.424	.086	.099
6: Disease-related rewards	4.74	1.25						1.000	-.052	.385	.001
7: Fear (disease)	3.83	1.58							1.000	.066	.588
8: Fear (vaccination)	4.83	1.44								1.000	.003
9: perceived threats	2.99	1.07									1.000

Table 4: Descriptive statistics for the unvaccinated sample and correlations among variables

Notes. N = 290; M = mean; SD = standard deviation

Table 5 provides a summary for participants who were twice-vaccinated at the time of data collection.

	Mean	SD	1	2	3	4	5	6	7	8	9
1: Perceived norms	5.12	1.56	1.000	.399	.424	.308	.108	-.332	.297	-.211	.108
2: Intention	4.49	.86		1.000	.819	.588	.346	-.558	.303	-.563	.106
3: Attitude (vaccination)	5.78	1.45			1.000	.689	.224	-.591	.293	-.590	.147
4: Perceived efficacy	5.69	1.17				1.000	.171	-.504	.178	-.557	-.019
5: Attitude (disease)	6.04	1.70					1.000	-.167	.282	-.207	.152
6: Disease-related rewards	2.45	1.36						1.000	-.180	.557	.027
7: Fear (disease)	4.64	1.70							1.000	-.008	.487
8: Fear (vaccination)	2.27	1.51								1.000	.064
9: Perceived threats	3.41	.99									1.000

Table 5: Descriptive statistics for the twice-vaccinated sample and correlations among variables

Notes. N = 290; M = mean; SD = standard deviation

4.4.2 Hypothesis testing

The mean values of intention to vaccinate were 2.59 for the unvaccinated and 4.49 for the twice-vaccinated, confirming that intention to vaccinate was higher for twice-vaccinated individuals than for unvaccinated individuals. We then used the model to calculate the results for the hypotheses for each group. Table 6 shows the results for each group.

	Original Value (Sig.; f²-value) Unvaccinated	Original Value (Sig.; f²-value) Twice-Vaccinated	CI [5%,95%]	Original difference (Sig. Group Differences)
H1a: perceived threats → fear (COVID-19)	.550*** (f^2=0.418)	.452** (f^2=0.288)	[-.260,.228]	.098ns
H1b: perceived threats → intention to vaccinate	.094ns (f^2=0.014)	-.009ns (f^2=0.000)	[-.132,.129]	.104ns
H2a: disease-related rewards → fear (COVID-19)	-.015ns (f^2=0.000)	-.135ns (f^2=0.023)	[-.215,.210]	.120ns
H2b: disease-related rewards → intention to vaccinate	-.166ns (f^2=0.043)	-.073ns (f^2=0.013)	[-.225,.213]	-.092ns
H3: fear (COVID-19) → attitude (COVID-19)	.423*** (f^2=0.218)	.281** (f^2=0.078)	[-.253,.254]	.143ns
H4: attitude (COVID-19) → intention to vaccinate	.067ns (f^2=0.008)	.159*** (f^2=0.085)	[-.122,.117]	-.092ns
H5a: perceived efficacy → fear (vaccination)	-.426*** (f^2=0.195)	-.600*** (f^2=0.490)	[-.167,.176]	.174ns
H5b: perceived efficacy → attitude (vaccination)	.507*** (f^2=0.317)	.513*** (f^2=0.387)	[-.250,.225]	-.007ns
H5c: perceived efficacy → intention to vaccinate	.042ns (f^2=0.002)	.078ns (f^2=0.010)	[-.357,.381]	-.035ns
H6: fear (vaccination) → attitude (vaccination)	-.054ns (f^2=0.004)	-.248** (f^2=0.099)	[-.262,.232]	.195ns
H7: attitude (vaccination) → intention to vaccinate	.503** (f^2=0.273)	.674*** (f^2=0.613)	[-.475,.406]	-.171ns
H8a: perceived norms → perceived threats	.147ns (f^2=0.022)	.084ns (f^2=0.007)	[-.268,.297]	.063ns
H8b: perceived norms → fear (COVID-19)	.122ns (f^2=0.022)	.221** (f^2=0.061)	[-.252,.217]	-.099ns
H8c: perceived norms → attitude (COVID-19)	.115ns (f^2=0.016)	.028ns (f^2=0.001)	[-.230,.243]	.087ns
H8d: perceived norms → intention to vaccinate	.093ns (f^2=0.014)	.048ns (f^2=0.007)	[-.128,.130]	.045ns
H8e: perceived norms → attitude (vaccination)	.208ns (f^2=0.064)	.187** (f^2=0.076)	[-.156,.160]	.022ns
H8f: perceived norms → fear (vaccination)	.058ns (f^2=0.004)	-.004ns (f^2=0.000)	[-.213,.210]	.062ns

H8g: perceived norms → perceived efficacy	.332** (f^2=0.124)	.363*** (f^2=0.152)	[-.186,.184]	-.031ns
H8h: perceived norms → disease-related rewards	-.094ns (f^2=0.009)	-.336*** (f^2=0.128)	[-.194,.188]	.242*

Table 6: Path coefficients and confidence intervals according to the hypotheses

*Notes. * < 0.05; ** < 0.01; *** < 0.001; one-tailed tests, ns denotes a non-significant difference at 0.05.*

Although there are other significant connections in Table 6, Figure 9 presents only the significant path coefficients leading to the determination of intention to vaccinate according to the research model.

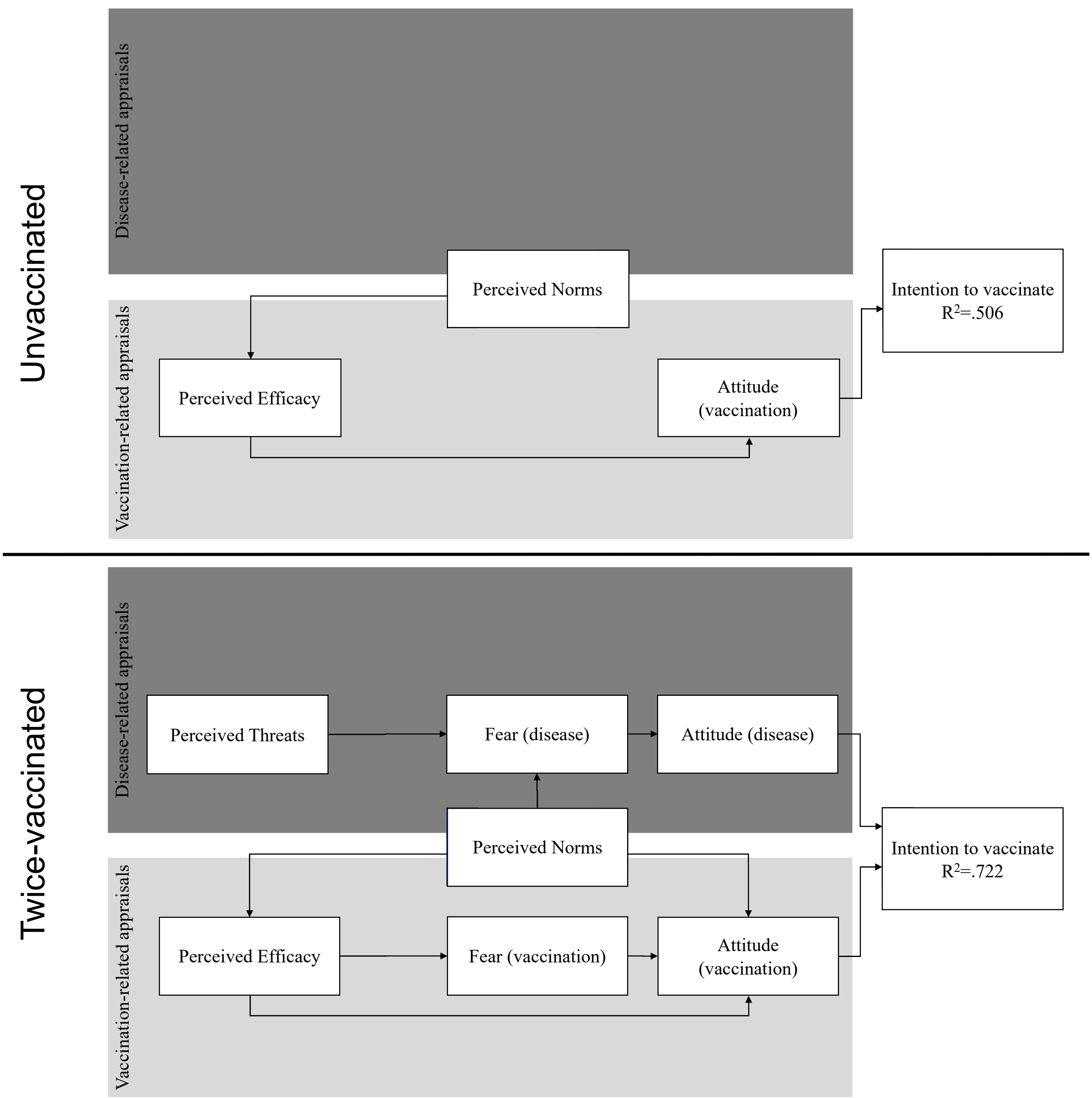

Figure 9: Hypothesis testing results (significant paths only)

We first considered the unvaccinated, for whom only vaccination-related appraisals were important for predicting vaccinating intention. More precisely, for unvaccinated participants, only attitude (toward vaccination) influenced intention to vaccinate. Attitude (toward vaccination) was in turn influenced by perceived efficacy. Perceived efficacy was influenced by perceived norms. Thus, for the unvaccinated group, our results support H1a, H3, H5a, H5b, H7, and H8g and do not support H1b, H2a, H2b, H4, H5c, H6, H8a-f, and H8h (see Table 6).

In contrast, for the twice-vaccinated, both vaccination-related and disease-related appraisals influenced the intention to vaccinate. The results show that both attitude (toward vaccination) and attitude (toward disease) affected the intention to vaccinate. First, attitude (toward vaccination) was influenced by perceived norms and perceived efficacy and negatively affected by fear (of vaccination). Second, attitude (toward disease) was influenced solely by fear (of disease), which was affected by perceived threats, and perceived norms. Thus, for twice-vaccinated participants, our results support H1a, H3, H4, H5a, H5b, H6, H7, H8b, H8e, H8g, and H8h and do not support H1b, H2a, H2b, H5c, H8a, H8c-d, H8f (see Table 6).

4.5 Discussion

In this study, we investigated the intention of different target groups to (re)vaccinate by focusing on two aspects, namely disease, and vaccination. Our results indicate that our integrated theoretical framework is appropriate for investigating the intention to vaccinate. For the unvaccinated participants, the results explained 50.6% of intention to vaccinate ($R^2 = .506$); for twice-vaccinated participants, they explained 72.2% ($R^2 = .722$). According to Hair et al. (2019), R^2 values of .75 can be considered substantial, and values of .50 moderate. Variance in other vaccination studies often varies between 50% and 70%. Thus, in terms of intention to vaccinate, our model has higher explanatory power than most existing literature. The results of Shiloh et al. (2021) explained 85% (R^2=.85), those of Shmueli (2021) explained 78% (R^2=.78), and those of Eberhardt and Ling (2021) explained 75% (R^2=.75). However, these studies investigated behavioral reasoning for intention to vaccinate and focused only on the vaccination-related appraisal aspects. They did not indicate the perceived effects of the disease on intention to vaccinate as disease-related appraisals. Our results further indicate that disease-related appraisals are important for the decision-making process of individuals and should therefore be investigated for vaccinations. Moreover, we advance beyond the work of Eberhardt and Ling (2021), who included only individuals who reported not having had the COVID-19 vaccination as well as limit their model to PMT only.

The results of Chu and Liu (2021), who used EPPM alongside HBM, a transtheoretical model, and TPB as a duality approach, explained 82.1% of intention to vaccinate (R^2=.821). As in our study, they used disease-related appraisals to refer to COVID-19, and the other reference object was vaccination. We did not focus on health-related variables such as weight or smoking, as Shmueli (2021) did, nor did we focus on vaccination hesitancy, as Chu and Liu (2021) did. Instead, we measured not only attitudes (toward vaccination) but also attitudes (toward disease). We included both fear (of disease) and fear (of vaccination) in our integrated theoretical framework because these variables are important for understanding vaccination intention. In general, attitude (toward disease) is a major predictor for intention to vaccinate (e.g., Gust et al., 2004). Given that there is as yet no evidence for long-term side effects, safety, and duration of protection for COVID-19 vaccines (Fernandes et al., 2021), it is particularly important to investigate attitude in this context.

By comparing our two groups regarding the intention to vaccinate, we uncovered differences in decision-making between unvaccinated and twice-vaccinated individuals. Concerning the explained variance of intention to vaccinate, we observe that, for unvaccinated individuals, other factors influence the vaccination decision. Although we did not consider these in the present study, there are references in the literature to the influence of conspiracy theories on the vaccination decision (e.g., Eberhardt & Ling, 2021).

In our study, the mean value of intention to vaccinate was 2.59 for unvaccinated participants and 4.49 for twice-vaccinated participants (measured on a five-point Likert scale). Thus, we conclude that twice-vaccinated individuals are more likely to get revaccinated than unvaccinated individuals are to get vaccinated initially. Chu and Liu (2021) found that the mean value of intention to vaccinate against COVID-19 was 3.98 (measured on a five-point Likert scale). Their results were based on data collected in early September 2020, when no vaccine against COVID-19 was available (Mathieu et al., 2021). Accordingly, all participants in their study were unvaccinated and most intended to get vaccinated (Chu & Liu, 2021). To the best of our knowledge, ours is the only study to address the intention to vaccinate against COVID-19 with both unvaccinated and twice-vaccinated individuals. Furthermore, we find a higher mean intention for twice-vaccinated individuals than did Chu and Liu (2021) study, which suggests that the intention to vaccinate may vary according to period, country, and culture (Li et al., 2021).

Concerning our model and vaccination-related appraisals, attitude (toward vaccination) influenced the intention to vaccinate in both groups. For the unvaccinated, attitude (toward vaccination) was the sole variable to predict intention to vaccinate. Attitude (toward vaccination) was determined by perceived efficacy. In contrast, for the twice-vaccinated, attitude (toward vaccination) was also determined by perceived norms and perceived efficacy and fear (of vaccination). Given that a range of COVID-19 vaccines was available at the time of our survey (EuropeanCommission, 2022), our results confirm the perception that unvaccinated individuals were reluctant to vaccinate because of their attitude toward COVID-19 vaccines (e.g., Chu & Liu, 2021). For twice-vaccinated individuals, in contrast, attitude (toward vaccination) had the most important influence on the intention to vaccinate, which also supports the results of Chu and Liu (2021).

Unlike the unvaccinated, the twice-vaccinated individuals were influenced in terms of attitude (toward vaccination) by fear (of vaccination). This may apply particularly to COVID-19 vaccination, because new vaccines are refused significantly more often than known vaccines (Wong et al., 2021). As COVID-19 vaccines were developed in a short time-span, many individuals have concerns and are hesitant to vaccinate (Vanderslott et al., 2022). Callaghan et al. (2021) argued that one reason for hesitance is that individuals prefer to wait for new vaccines that have been developed over a more extended period of time.

For both unvaccinated and twice-vaccinated individuals in this study, perceived efficacy influenced the intention to vaccinate. Perceived efficacy includes both perceived response efficacy and perceived behavior control. Perceived response efficacy is similar to perceived benefits and perceived usefulness (Gesk et al., 2021). Perceived benefits negatively influence decision-making processes, according to Mercadante and Law (2021). Our findings regarding perceived behavior control and perceived response efficacy support previous studies on the intention to vaccinate (e.g., Ling et al., 2019). However, those studies treated perceived response efficacy and perceived behavior control as unique variables for predicting intention to vaccinate (Ling et al., 2019). Here, in contrast, we found no direct impact on intention to vaccinate for either the unvaccinated or the twice-vaccinated. Therefore, we conclude that perceived efficacy is an important predictor of attitude (toward vaccination).

Concerning our model and disease-related appraisals, for the unvaccinated, there was no influence on intention to vaccinate. In contrast, disease-related appraisals influenced the intention of the twice-vaccinated to get vaccinated. Notably, attitude (toward disease) affected the intention to vaccinate of twice-vaccinated individuals. We suggest that exceptionally high non-monetary costs or undesirable side effects negatively impacted the vaccination decision (Ling et al., 2019).

Our findings for the twice-vaccinated also contradict the only relevant study on fear (Chu & Liu, 2021), according to which fear (of COVID-19) is of central importance, as it prevents actions (i.e., vaccinations). Chu and Liu argued that individuals tend to ignore the threat of COVID-19 and not feel overwhelmed by COVID-19-related restrictions.

To explain fear (of vaccination), we investigated disease-related rewards, asking whether individuals preferred to wait for a new COVID-19 vaccine developed over a longer time (see appendix). Surprisingly, disease-related rewards significantly influenced the intention to vaccinate against COVID-19 for both, unvaccinated and twice-vaccinated individuals. Thus, our results disagree with those of Thunström et al. (2021) in showing that individuals do not intend to vaccinate because of the immature development of new vaccines in general.

In our model, perceived threat includes perceived severity and perceived vulnerability. For the twice-vaccinated, perceived threat influenced fear (of disease). Both Li et al. (2021) and Chu and Liu (2021) found that perceived severity and perceived vulnerability did not affect the intention to vaccinate. In contrast, Shmueli (2021) observed an influence of both factors on the intention to vaccinate. For unvaccinated individuals, perceived threats of disease did not influence intention to vaccinate if perceived threats were not high. Therefore, we concur with the findings of Fall et al. (2018) that perceived vulnerability to a disease is insufficient to prompt the decision to vaccinate. Similar results were obtained by Hsu et al. (2009), who found that intention among young women to get vaccinated against HPV was relatively low because of their low perceived threat of disease (women aged 50 years and older are more likely to develop HPV-related cancer; Hsu et al. (2009)). We deduce from this that a certain level of threat is necessary to prompt individuals to decide to get vaccinated.

For both groups, perceived norms were essential for predicting the intention to vaccinate. In contrast to Marra et al. (2016), Guidry et al. (2021), and Shmueli (2021), we found that perceived norms did not directly influence intention to vaccinate for either the unvaccinated or the twice-vaccinated. Nonetheless, perceived norms had an indirect influence. In the case of the unvaccinated, perceived norms influenced perceived efficacy. In contrast for the twice-vaccinated, perceived norms influence perceived efficacy, attitudes (toward vaccination), and fear (of disease). For this reason, perceived norms are also an important predictor of intention to vaccinate.

Ultimately, comparison of unvaccinated individuals with twice-vaccinated individuals shows that attitude (toward vaccination) is essential for predicting intention to vaccinate. In contrast to being unvaccinated, attitude (toward disease) is a significant factor in determining whether to get revaccinated. If the attitude (toward vaccination) is positive, twice-vaccinated individuals also positively intend to vaccinate. The more negative attitude (toward disease), the more likely the twice-vaccinated are to decide to get revaccinated.

4.6 Conclusion

Given the importance of vaccination rates as a research topic worldwide (Wong et al., 2021), this study built an integrated theoretical framework for COVID-19 vaccinations to understand vaccination decision-making of both unvaccinated and twice-vaccinated individuals.

4.6.1 Theoretical Implications

Our results have four main theoretical implications. First, we show that the integrated theoretical framework is suitable for the context of vaccinations. Thus, integrating theories from healthcare and psychology is appropriate for understanding the intention to vaccinate of individuals who balance disease-related and vaccination-related appraisals. The explained variance results show that the duality approach helps understand reasoning better and allows us to understand which factors are important in balancing vaccination-related and disease-related appraisals. Therefore, the integrated theoretical model allows a better understanding of the decision-making process in relation to the intention to vaccinate.

Second, our results compare the behavioral reasoning of unvaccinated and twice-vaccinated individuals in relation to COVID-19 vaccinations. They show that intention to vaccinate is lower for unvaccinated individuals than for twice-vaccinated individuals who are about to receive a booster vaccination. The main difference between unvaccinated and twice-vaccinated individuals is that unvaccinated individuals root their behavioral intentions in vaccination-related appraisals only, whereas twice-vaccinated individuals consider both vaccination-related and disease-related appraisals. Hence, we confirm the findings of prior studies in relation to twice-vaccinated individuals and provide novel insights regarding unvaccinated individuals.

Third, our results confirm the finding of Gesk et al. (2021) that individuals consider vaccination-related appraisals for behavioral intention regarding innovations only; if individuals are familiar with the behavioral intention in question, they use vaccination-related and disease-related appraisals to determine behavioral intention. Our findings support this conclusion by showing that unvaccinated individuals (i.e., individuals inexperienced in getting vaccinated against COVID-19) considered only vaccination-related appraisals in arriving at their vaccination intention. In contrast, twice-vaccinated individuals (i.e., individuals experienced in getting vaccinated against COVID-19) considered both vaccination-related and disease-related appraisals. Thus, our investigation of the duality approach in non-technical medical situations suggests that a focus on both disease and vaccination aspects should be employed to help twice-vaccinated individuals make vaccination decisions.

Fourth, our results indicate that it is helpful to use the duality approach, which leads to a longer questionnaire. Models seeking to use a new treatment only as a reference object might miss relevant explanatory factors, as it is unclear under which conditions a new treatment will be perceived as sufficiently novel.

4.6.2 Practical Implications

Our findings have three main practical implications for the COVID-19 vaccination strategy. First, perceived efficacy impacts the intention to vaccinate indirectly. For this reason, a targeted communication strategy should provide factual information to everyone in a simple, transparent, and understandable way. It should include precise information about the individual vaccines available, including efficacy rates and similarities and differences, taking care to explain new vaccine techniques.

Second, one element in the perceived efficacy of vaccination is how easy the vaccine is to access. As perceived efficacy influences attitude (toward vaccination), vaccinations should be made as accessible as possible, and should preferably be obtainable with little effort (e.g., in places frequently visited by many individuals). Where the number of vaccination doses available is limited, vaccination appointments could be assigned to minimize waiting time, with an option for individuals to cancel their appointments if they wish.

Third, with perceived norms influencing perceived efficacy of vaccination for unvaccinated and to distribute correct information, the communication strategy should take all age and social groups into account. For each of these groups, correct and sufficient information on the efficiency of vaccination should be provided by a medium that is appropriate to address them, e.g., print and social media.

4.6.3 Limitations and Future Research

As with any investigation, our research has several limitations. First, we designed our survey for the context of COVID-19 vaccinations, a situation that may differ from other diseases or vaccinations and produce different results. The vaccinations against COVID-19 that are widely available are based on mRNA technology, a technique not used in vaccinations until now, and several doses over a short time-span are necessary for whole populations (Vanderslott et al., 2022). Despite the availability of vaccines in many countries, with millions of people already vaccinated successfully, substantial percentages of some populations are unwilling to get vaccinated (EuropeanCommission, 2022; Vanderslott et al., 2022) or reluctant to receive a booster (Wong et al., 2021).

Second, the vaccination status of our participants is self-reported and may therefore be incorrect. To mitigate this concern, we used an anonymous survey, and we included attention check items. The data for 36 individuals who had already received booster vaccinations were excluded. Hence, we are confident that our participants' responses were accurate.

Third, the empirical design of our study is cross-sectional which is a limitation as respondents reported on all variables at one point in time. The design was chosen as the situation with vaccinations was quite dynamic with lots of intensive discussions and campaigns going on and measuring with two points in time would have placed the analysis outside of this time period. We have to note that despite all actions to avoid common method bias (e.g. order of questions) our data may be subject of this bias.

Fourth, the measurement of attitude regarding the disease used a negative wording while the scale remained in an ascending order. Participants might have overseen the reversed rating for this variable. However, the descriptive results show that the absolute values are high while attitude regarding the vaccination is high as well, indicating that participants answered also these questions appropriately.

Fifth, as Fishbein and Ajzen (2010) noted, it is necessary to focus on specific factors that influence the intention–behavior gap, which entails a lack of focus on other factors. Thus, in the present study we did not analyze the nature or quality of our participants' information-gathering activities, despite the importance of this for determining behavioral intention (Fishbein & Ajzen, 2010; Shiloh et al., 2021). Hence, among our participants, group constraints on opinions and self-selection processes of misinformation and information may have significantly influenced the intention to vaccinate. Further, there are more behavioral theories towards vaccination that could have been considered in our integrated theoretical model (Betsch et al., 2018; Weber et al., 2021). Moreover, we did not examine trust in government, which many studies have shown plays an essential role in the intention to vaccinate, especially when vaccination is refused (e.g., Thunström et al., 2021). Nor did we examine gender differences. Previous studies have determined that women are less often vaccinated than men (e.g., Thunström et al., 2021). Similarly, although other studies have observed that differences in ethnicity lead to differences in intention to vaccinate (e.g., Callaghan et al., 2021), our study was limited to Germany; investigating other countries could lead to different results.

Future research could use our approach for comparisons between different groups to identify the critical variables in the decision-making process regarding vaccination. In particular, applying our approach to countries other than Germany will yield results that could be compared to ours to investigate behavioral intentions toward vaccination in different cultures.

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4.8 Appendix

The questionnaire, the data as well as the detailed results of the analyses can be found here: http://dx.doi.org/10.17192/fdr/154.

5 Framed Information in Medical Decisions for AI-based HIS: Balance between Adaptive and Non-Adaptive Appraisals[8]

Tanja Sophie Gesk

Abstract

AI-based health information systems (HIS) in diagnostics could be implemented first in medical field. AI-based HIS are already more accurate than physicians. However, individuals still choose the physician more often. In this study, we want to find out what influence positively and negatively framed information has on the decision for or against AI-based HIS. The positive information is the success rate and the negative information is the error rate of the AI-based HIS and the physician. It is shown that positive information had a negative influence, but negative information had a positive influence on intention to use HIS. Using an integrated theoretical framework with a duality approach, it can be seen that adaptive appraisals influence the intention to use. In particular, attitudes toward HIS and perceived efficacy are key factors in the medical decision-making. This knowledge can be used to persuade patients for more effective diagnosis through an AI-based HIS.

[8]This article is in preparation for submission.

5.1 Introduction

Patients' acceptance is critical for the proper adoption of artificial intelligence (AI)-based health information systems (HIS) in medical applications (Dai & Tayur, 2022; Yun et al., 2021). AI-based HIS can provide medical diagnoses and treatment recommendations with high accuracy and low cost, which can lead to significant welfare gains (Lawrence et al., 2022). Accordingly, AI-based HIS is a promising innovation in radiological diagnostics. Therefore, AI-based HIS are likely to be used in radiological diagnostics sooner than in other medical fields (Pesapane et al., 2018).

AI-based HIS can improve the quality of healthcare by reducing human errors (Aggarwal et al., 2023; Barrett et al., 2019). Several medical studies have already shown that decision-making by AI-based HIS is often significantly more accurate than that of physicians (Itri & Patel, 2018; Loftus et al., 2020; Rauschecker et al., 2020; Rosenberg et al., 2018). When AI-based HIS take over routine tasks, physicians have the opportunity to provide more intensive care to patients or perform more frequent tests on high-risk patients (Yu et al., 2018). Nevertheless, individuals often choose a physician over a more accurate AI-based HIS (Lennartz et al., 2021; Yokoi et al., 2021). This behavior occurs particularly in contexts relevant to prognosis and is referred to as an avoidance algorithm (Dietvorst et al., 2015).

However, certain information can also influence the decision for or against an AI-based HIS (the so-called framing effect). The framing effect is a cognitive bias that states that negative and positive information can induce different behaviors (Akl et al., 2011; Cunneen et al., 2019). This can ultimately lead to a change in opinion (Peng et al., 2013; Tversky & Kahneman, 1981). The framing effect has been studied extensively in the context of medical decisions (e.g., Peng et al., 2013). However, the focus has often been just on the decision. In particular, in medical decision-making, individuals weigh benefits and harms (Resnik, 2004; Say et al., 2006). The individual's own body is the output of the decision (Lewis & Holm, 2022). In addition, positively or negatively framed information can influence medical decision-making (Gong et al., 2013; Peng et al., 2013). The effect of positive and negative information on the benefit-harm trade-off leads to the first research question:

RQ1: *(a) What is the influence of framed information on patients' medical decision-making when using AI-based HIS in diagnostics? (b) How often does switching between physician and AI-based HIS occur due to the influence of negative or positive framed information?*

Furthermore, Gesk et al. (2021) show that there are differences in patients' medical decision-making between the decision of a surgery by a physician, a physician with AI support, and an

AI only. In a similar study, Gesk et al. (2022) examined the intention to use AI-based applications to help patients manage diabetes. Again, medical decision-making was examined by comparing patients' diabetes management with a physician, a physician with AI support, and AI alone. The context of these studies are situations where the individual is in direct (physical) contact with the physician or the AI-based HIS. According to Gesk et al. (2021) and Gesk et al. (2022), as the proportion of an unknown technology (e.g., AI-based HIS) increases in medical decision-making, individuals focus on the aspects related to the unknown technology. As the proportion of the unknown technology increases, individuals focus less and less on the aspects of the disease (Gesk et al., 2021, 2022). This decision behavior has not been studied in remote medical situations, such as diagnosis. This leads us to the second research question:

RQ2: *(a) Whether AI-based HIS is accepted for diagnostics, and (b) why AI is accepted or rejected in that context?*

The structure of this paper will be as follows. First, we review studies to the framing effect as well as on understanding (medical) decision-making regarding AI and physicians. Then, we describe the integrated theoretical framework of Gesk et al. (2021), which is the basis of our investigation. Next, we describe our materials and methods, presenting our questionnaire, sample, and data analysis. Then, we offer our findings, including descriptive statistics and hypothesis testing results. After discussing these findings, we conclude with theoretical and practical implications, limitations of the study, and directions for future research.

5.2 Theoretical Background

5.2.1 (Medical) Framing Effect

Tversky and Kahneman (1981) use prospect theory to show the influence of framed information on decision-making. The so-called framing effect is a cognitive bias that negative or positive information can induce different behavior (Akl et al., 2011; Ho, 2021). When making decisions about losses, individuals are more likely to choose a risky option (Cunneen et al., 2019). However, when making decisions about gains, individuals are more likely to choose a risk-averse option (Kühberger & Tanner, 2010; Tversky & Kahneman, 1981). Levin et al. (1998) define three types of framing effects: attribute framing (positive and negative information), goal framing (presentation of the consequence of action or inaction), and risky choice framing (decision between two options where one option is associated with a loss to the individual) (Levin et al., 1998).

The framing effect has been extensively studied in medical decisions (Peng et al., 2013). The three types of framing effects according to Levin et al. (1998) can also be found in the medical context (Krishnamurthy et al., 2001). Medical advice is more likely to be followed when information is presented with a focus on the consequences of not following the advice (loss), rather than the benefits of following the advice (gain) (Peng et al., 2013). The goal of an AI-based HIS should be the maximization of benefits with the minimization of risks (AI-HLEG, 2019).

5.2.2 Related Work towards Medical Framing Effect

Individuals were more likely to choose a treatment when confronted with the probability of death rather than the probability of survival (Peng et al., 2013). The same effect occurs with complementary treatments. Patients are more likely to choose these complementary treatments when faced with the negative consequences of not receiving treatment (Tang & Chooi, 2021). For new drugs, patient and physician trust increases most when negative framing is used (Perneger & Agoritsas, 2011).

In contrast, according to Gallagher and Updegraff (2012), preventive behavior is more likely to occur with positively framed information than with negatively framed information. Patients are more likely to undergo surgery when the probability of survival is focused. Thus, when the probability of non-survival is presented, individuals perceive surgery as more risky (McNeil et al., 1982; Tang & Chooi, 2021). Further, Akl et al. (2011) show in a review that loss-to-follow messages led to more positive perceptions of efficacy. Therefore, we hypothesize the following:

H1a: Positive framed information positively influences the choice of AI.

In contrast, according to Dietvorst et al. (2015), individuals lose trust in AI faster than humans when AI makes mistakes. This leads us to the following hypothesis:

H1b: Negative framed information negatively influences the choice of AI.

5.2.3 Understand the Medical Decision-Making by Using Integrated Theoretical Framework

Particularly in the medical context, individuals behave irrationally in part because their own bodies are the outcome of their decision (Lewis & Holm, 2022). Several medical studies (e.g., Loftus et al., 2020; Rauschecker et al., 2020) have already shown that AI-based HIS decisions are often significantly more accurate than those of human physicians. Especially in the medical context, the recommendation or diagnosis of a physician is preferred to that of an AI-based HIS. According to Longoni et al. (2019), individuals are more likely to trust the physician because they assume that AI-based HIS will neglect their physical uniqueness, including medical (family) history. Further, Seitz et al. (2022) examine patients' trust in a diagnostic chatbot and a telemedicine physician. They find that there are significant differences in trust towards a physician and an AI-based HIS. The physician is trusted more due to his/her qualifications and for affective reasons, even when the individual is aware of the irrationality. Therefore, Seitz et al. (2022) conclude that emotions play an important role in a medical situation. Dietvorst et al. (2015) also show that individuals prefer human prognosticators to AI, even when they know that AI is more accurate than a human. One reason for this so-called algorithm aversion is that individuals lose trust in AI more quickly than in human forecasters, even though they know that AI is less prone to error. Individuals are more likely to use AI when they do not perceive AI errors (Dietvorst et al., 2015). According to Yokoi et al. (2021), the physician is trusted more than the AI-based HIS for the same treatment performance. This may be due to individual's beliefs, which range from the great potential for healthcare to strong fears of negative effects on individuals and society, according to Richardson et al. (2022). One fear is that AI-based HIS will be subject to social biases and discriminate against individuals with disabilities (Richardson et al., 2022). This may be explained by the fact that there is a sense of collaboration and shared responsibility for treatment decisions when a physician diagnosed a patient (Promberger & Baron, 2006). In contrast, individuals show algorithm appreciation according to Logg et al. (2019). This means that individuals prefer the evaluation of an AI over that of a human and even over their own assessment. Zhang et al. (2021) also show that individuals tend to have a positive attitude toward AI-based HIS in the medical field.

Thus to answer the second research question, when and why AI-based HIS are accepted in diagnostics, we use the integrated theoretical framework of Gesk et al. (2021). The integrated theoretical framework developed by Gesk et al. (2021) combines eight theories from three perspectives that examine the intention to use. First, from the health perspective, the health belief model (Hochbaum, 1958; Rosenstock, 1974b), protection motivation theory (Floyd et al., 2000; Rogers, 1975), and extended parallel processing model (Storey et al., 2008; Witte, 1994) are used. Second, from the technology perspective, the unified theory of technology acceptance 2 (Venkatesh et al., 2012), and the technology acceptance model (e.g., Davis, 1989; Venkatesh & Davis, 2000) are used. Third, from the psychological perspective, the theory of planned behavior (Ajzen, 2020), the psychological reactance theory (Brehm, 1966), and the reasoned action approach (Fishbein & Ajzen, 2010) are applied.

The basis of the integrated theoretical framework of Gesk et al. (2021) is the dual approach of adaptive and non-adaptive appraisals (see Witte, 1994). That is, individuals must decide whether to accept a particular treatment with an AI-based HIS (referred to adaptive appraisals) or to reject the treatment and engage in unhealthy behaviors (referred to non-adaptive appraisals) (Gesk et al., 2021; Gücin & Berk, 2015). Individuals weigh adaptive and non-adaptive appraisals when making decisions (Gesk et al., 2021, 2022). Further, behavior related to evaluations of AI-based HIS is cognitive, whereas behavior related to the potential serious illness is more emotional (Witte, 1994). For example, individuals must weigh whether to seek an evaluation from an AI-based HIS or a physician to clarify their headaches.

With this framework, we aim to analyze the relevant factors that influence medical decision-making in diagnostic evaluation by a physician or an AI-based HIS. The advantage of the integrated theoretical framework is the use of the duality approach, which considers the non-adaptive appraisals and the adaptive appraisals in the decision-making process. According to Resnik (2004) and Gesk et al. (2021), individuals trade-off between harms and benefits, especially in medical decision-making. In order to investigate this trade-off, we use non-adaptive appraisals that take into account disease-related aspects (Gesk et al., 2021). In this study, the reference object is the suspicion of a serious brain disease. On the other hand, adaptive appraisals refer to the type of diagnosis (Gesk et al., 2021). In this study, the reference object is either the appraisals by a physician or by an AI-based HIS.

The perceived threat of a disease results from both perceived severity and perceived vulnerability (Gesk et al., 2021). Especially for potentially life-threatening diseases, physicians recommend all diagnostic tests to rule out even rare diseases (Itri & Patel, 2018). An individual's perceived threat of the disease increases fear of the disease (Krusemark & Li, 2011). Fear is a transient emotional state that is also influenced by fear of negative consequences (Bratić et al., 2021; Venkatesh et al., 2012). Therefore, the perceived threat of a disease may also contribute to the intention to use HIS that can eliminate or at least mitigate the negative consequences of the disease (Floyd et al., 2000; Krusemark & Li, 2011). This leads us to the second hypothesis:

> *H2: Perceived threats have (a) a positive influence on fear (of disease) and (b) a positive influence on intention to use HIS.*

This is in contrast to the benefits of not using the new HIS for diagnosis (Gesk et al., 2022; Vance et al., 2012). The so-called non-adaptive rewards minimize the fear of the disease and also reduce the intention to use the HIS (Gesk et al., 2021):

> *H3: Non-adaptive rewards have (a) a negative influence on fear (of disease) and (b) a negative influence on intention to use HIS.*

In addition, fear of the disease can have a negative impact on the individual's sense of security and related attitudes toward the disease (Gesk et al., 2021). Attitudes toward disease, as a positive or negative opinion about a particular word (Venkatesh et al., 2012), are assumed to be adversely affected by the emotion of fear, leading to the fourth hypothesis:

H4: Fear (of disease) positively influences attitude (toward disease).

According to Fishbein and Ajzen (2010), attitude is the most important indicator of intention to use. Therefore, like Gesk et al. (2021), we hypothesize that attitude toward the disease has a direct influence on intention to use in the non-adaptive appraisals. This leads to the fifth hypothesis:

H5: Attitude (toward disease) positively influences intention to use HIS.

Based on (early) diagnostics, suspected (rare) diseases can be clarified at low cost (Itri & Patel, 2018). The use of AI-based HIS can improve the quality of healthcare, especially in diagnostics (Gerlings et al., 2022). AI-based HIS already demonstrate the highest levels of reliability and dependability (Coppola et al., 2021). Similarly, more effective treatment interventions can be selected. As a result, treatments can be started earlier, which either mitigates or eliminates the consequences of the disease (Chen et al., 2020; Gerlings et al., 2022; Itri & Patel, 2018). Therefore, the sixth hypothesis is:

H6: Perceived efficacy has a negative influence on (a) fear (of HIS) and a positive influence on (b) attitude (toward HIS) and on (c) intention to use HIS.

Fear may arise not from the disease but from the unknown (Gesk et al., 2021). For example, a physician's blind trust in AI-generated outcomes (Ellahham et al., 2020) or fear of a misprogrammed AI-based HIS (Coppola et al., 2021) may cause this emotional state in patients. This brings us to the seventh hypothesis:

H7: Fear (of HIS) negatively influences attitude (toward HIS).

Further, attitudes toward HIS are considered the most important indicator of adaptive appraisals (Fishbein & Ajzen, 2010; Gesk et al., 2021). Accordingly, the eighth hypothesis reads:

H8: Attitude (toward HIS) positively influences intention to use HIS.

Perceived norms cannot be counted exclusively as either adaptive or non-adaptive appraisals and influence each variable of adaptive and non-adaptive appraisals (Gesk et al., 2021). In addition, perceived norms also count as an important indicator of intention to use HIS (Fishbein & Ajzen, 2010). Accordingly, the ninth hypothesis is:

H9: Perceived norms have a positive influence on (a) perceived threats, (b) fear (of disease), (d) intention to vaccinate, (e) attitude (toward HIS), and (g) perceived efficacy, and a negative influence on (c) attitude (toward disease), (f) fear (of HIS), and (h) non-adaptive rewards.

Figure 10 provides an overview of the integrated theoretical framework and its hypotheses.

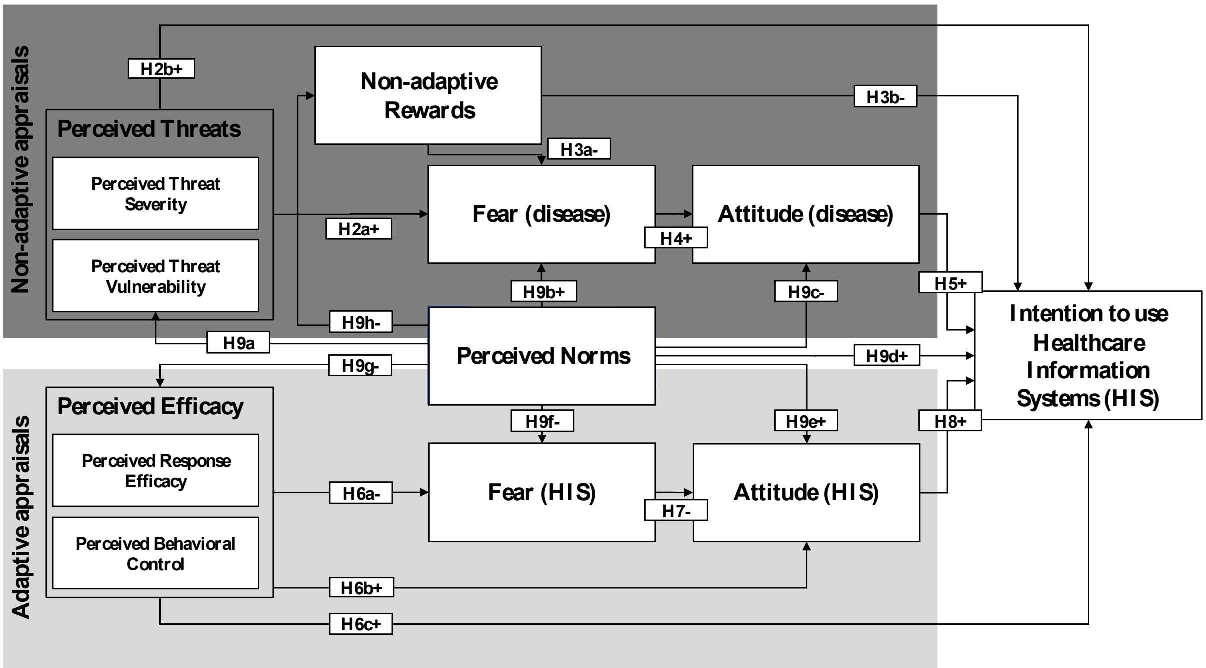

Figure 10: Integrated theoretical framework and hypotheses adapted from Gesk et al. (2021)

5.3 Materials and Method

5.3.1 Study Design

To analyze the hypotheses, we chose the medical diagnosis of a magnetic resonance imaging (MRI) scan made by an AI-based HIS. We did this because there are objective accuracy comparison studies between an AI-based HIS and physicians (e.g., Rauschecker et al., 2020). Thus, we used attribute framing to examine individual decision-making in terms of the success or failure rate of the AI-based HIS and the physician according to the results of Rauschecker et al. (2020).

We used a quasi-experimental research design in which participants (recruited online via Clickworker, a marketplace for micro-tasks) went through a fictional decision scenario. The scenario was pre-tested with 50 probands to ensure a realistic and challenging decision context. The probands were asked to imagine that they had been suffering from headaches for a long time. An MRI scan would provide certainty about the cause. Furthermore, the control variable was selected in line with the recommendations of Goodman et al. (2012) regarding attentional control. Based on attention checks, probands were selected based on whether they understood the scenario correctly and found it sufficiently realistic. In addition to the scenario, the probands were given an introductory text about AI and MRI scans. Probands had the option of choosing between an AI-based HIS and a physician for diagnosis. Further, probands were then randomly assigned to receive either positively (success rate) or negatively (failure rate) framed information about the performance of the AI and the physician. This information was taken from Rauschecker et al. (2020). Rauschecker et al. (2020) investigate how AI and physicians correctly diagnose common and rare diseases in brain MRI scans. The AI-based HIS combines data-driven and domain-specific methods, including deep learning and Bayesian networks. Participants were then given the opportunity to choose between the AI-based HIS and the physician. In this way, we were able to observe whether the participants would change their original behavior as a result of the success/failure rate cue. Thus, the following eight groups occur based on the descript procedure:

a) No switching behavior: Physician-Physician with negative Information (Phy-Phy_Neg)
b) No switching behavior: Physician-Physician with positive Information (Phy-Phy_Pos)
c) No switching behavior: AI-AI with negative Information (AI-AI_Neg)
d) No switching behavior: AI-AI with positive Information (AI-AI_Pos)
e) Switching behavior: Physician-AI with negative Information (Phy-AI_Neg)
f) Switching behavior: Physician-AI with positive Information (Phy-AI_Pos)
g) Switching behavior: AI-Physician with negative Information (AI-Phy_Neg)
h) Switching behavior: AI-Physician with positive Information (AI-Phy_Pos).

5.3.2 Questionnaire

Subsequently, probands were then asked to answer questions based on the template of Gesk et al. (2021) on the following reflective and formative variables. The reflective variables are intention to use (three items), attitude (HIS) (five items), attitude (disease) (four items), perceived norms (four items), perceived behavioral control (three items), perceived HIS efficacy (three items), fear (HIS) (three items) and fear (disease) (three items). The formative variables are perceived severity (seven items), perceived vulnerability (four items), and non-adaptive rewards (three items). All items were measured on a seven-point Likert scale ("1 - strongly disagree" to "7 - strongly agree"). In addition, basic demographic information was collected (age, gender, general computer skills, technical knowledge of AI and experience with AI-based services). The questionnaire can be found in the Appendix.

5.3.3 Sample

Anyone can be in a diagnostic situation. Therefore, we used a convenience sample of 628 subjects. Since subjects were free to choose between a physician-based HIS and an AI-based HIS for both decisions, there had to be a minimum size for each group to analyze the results (Kock & Hadaya, 2018). Nevertheless, groups g) and h) have no or only few participants that they are not suitable for further analysis. For this reason, the analyses and interpretations are based on the data from groups a) through f). Figure 11 provides an overview of the sample division into the described groups.

In the total sample, 37.3% (n=234) of the participants were female, 61.9% (n=389) were male, and 0.8% (n=5) were diverse. The mean age was 38.93 years (SD: 11.327), with an age range of 18-68 years. The probands' self-assessed general computer skills averaged 4.27 (SD: .711), technical knowledge of AI averaged 3.35 (SD: .856), and average experience with AI-based services averaged 3.05 (SD: .937).

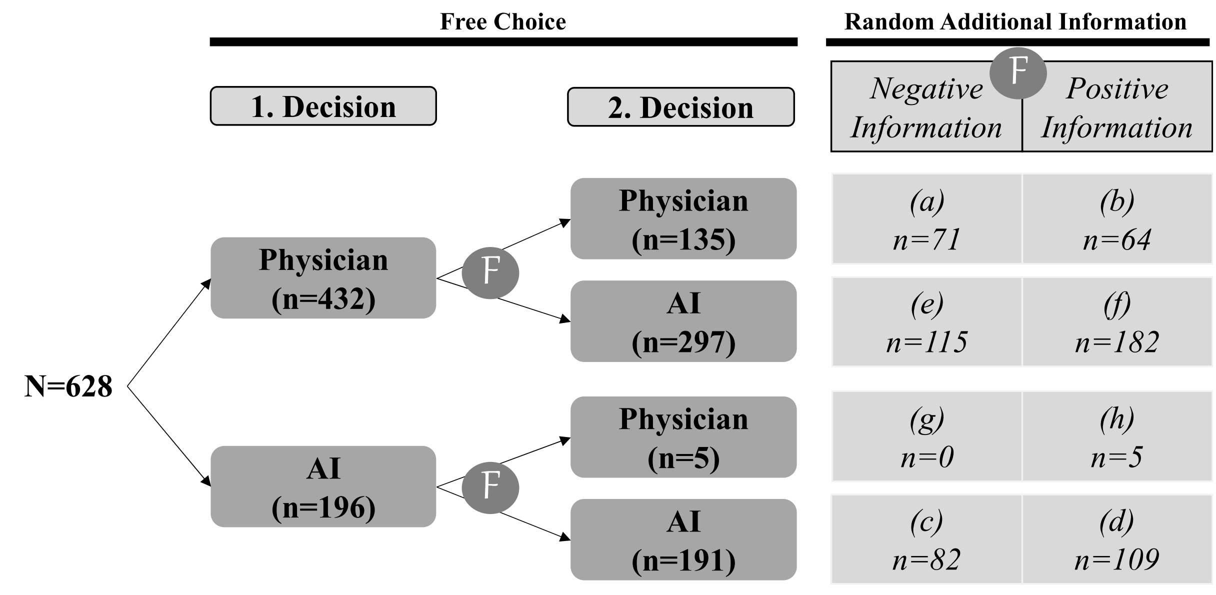

Figure 11: Research procedure and group size

Notes. F = Framing

5.3.4 Data Analyses

Regarding Hypothesis 1, we used binary logistic regression in IBM SPSS Statistic 27 to determine the switching behavior after the additional positive (Hypothesis 1a) and negative (Hypothesis 1b) information. This method of data analysis was chosen due to the binary nature of the dependent variable, as the decision to switch after the additional information was analyzed as yes and no (DeMaris et al., 2013). Using the omnibus test of the model coefficients (see Appendix), the significance is 0.025. Therefore, the model is suitable for further investigation of binary logistic regression. However, the classification table shows that the significance is low at 51.9% (see Appendix). Further, the mean values of the intention to use variable were compared using a test of homogeneity of variance and ANOVA in IBM SPSS Statistic 27 (see Appendix).

For the other hypotheses, the partial least squares method was used to analyze the data. This allows for the processing of structural equation models consisting of formative and reflective variables (Hair et al., 2019). At the same time, we followed the recommendations of Hair et al. (2021) for multigroup analysis in PLS-SEM to compare the six different groups. For this purpose, we performed a bootstrapping procedure and permutation tests with 5,000 replicate samples in SmartPLS 4.0.8.9 (Ringle et al., 2022). Following the data analysis procedure of Hair et al. (2019), we first analyzed the reflective measurement models, then the formative measurement models, and finally the structural model.

First, the reflective variables met indicator reliability criteria with loadings above 0.7 (see Appendix). Composite reliability was confirmed as scores were above 0.7. The average variance extracted was above 0.5 (see Appendix; Hair et al., 2019). Discriminant validity using the heterotrait-monotrait was also confirmed as the values were less than 0.9 (see Appendix; Henseler, Ringle, et al., 2014).

Second, the formative variables were tested. Convergent validity was present as outer weights and outer loadings were above 0.7 (see Appendix). Multicollinearity was found to be unproblematic as the variance inflation factors (VIF) were below 5 (see Appendix; Hair et al., 2019). By testing and confirming the significance of the weights and loadings, the relative and absolute importance of the indicators was examined (see Appendix).

Third, the structural model was tested for model fit using the standardized root mean square residual (Henseler et al., 2016). The saturated SRMR value of 0.098 was less than 0.1, which is considered a good fit according to Henseler, Ringle, et al. (2014). Collinearity (VIF) was also present as the values were higher than 5 (see Appendix; Hair et al., 2019).

Effect sizes were examined using Kock and Hadaya (2018) statistical power analysis through G*Power 3.1.9.6 (Mayr et al., 2007). Using the effect sizes of Cohen (1988), we adjusted the threshold to account for the small effect due to the sample size. Consequently, the threshold is f^2=0.089 for Phy-Phy_Neg, f^2=0.054 for Phy-AI_Neg, f^2=0.077 for AI-AI_Neg, f^2=0.034 for Phy-AI_Pos, and f^2=0.058 for AI-AI_Pos.

The coefficient of determination is considered weak for Phy-Phy_Neg (R^2=.428), Phy-AI_Neg (R^2=.365), Phy-AI_Pos (R^2=.436), and AI-AI_Pos (R^2=.399) according to Hair et al. (2019). However, AI-AI_Neg (R^2=.704) is considered moderate according to Hair et al. (2019). Furthermore, we applied the MICOM procedure of Hair et al. (2019) to test the invariance of the measurement model and the group significances. However, due to the different group sizes, the results of the multigroup analysis may be affected. In order to circumvent the family wise error rate this creates (Hair et al., 2018), we performed all currently available statistical multigroup analyses (parametric t-test, multigroup analysis, permutation). Table 7 shows the significant differences between each group and the results are presented in detail in the Appendix.

Constructs with significant differences	**… between negative and positive framing**	**… within negative framing**	**… within positive framing**
Attitude (disease)	AI-AI_Neg ←→ Phy-AI_Pos AI-AI_Neg ←→ AI-AI_Pos	-	-
Attitude (HIS)	-	-	-
Non-adaptive rewards	-	-	Phy-AI_Pos ←→ AI-AI_Pos
Perceived norms	-	-	-
Perceived efficacy	Phy-AI_Neg ←→ Phy-AI_Pos Phy-AI_Neg ←→ AI-AI_Pos AI-AI_Neg ←→ Phy-AI_Pos	Phy-Phy_Neg ←→ Phy-AI_Neg	-
Perceived threats	-	AI-AI_Neg ←→ Phy-Phy_Neg AI-AI_Neg ←→ Phy-AI_Neg	-

Table 7: Overview of significant differences between the groups

When analyzing the data, it became clear that the data from the group Phy-Phy_Pos were not meaningful. This lack of power could not be remedied by a larger sample. This was tested by duplicating the sample several times to lift potential effects out of the smaller sample size, but still no effect could be found. For this reason, we tested for heterogeneity using FIMIX-PLS segmentation according Hair et al. (2016). This showed that there was only one segment. Based on these analyses, we decided not to include this group in the analysis.

To check the PLS predictive power, we confirmed the PLS-SEM Q^2 prediction power according to Shmueli et al. (2019) for all groups. These results showed that there was no predictive power for AI-AI_Neg and Phy-Phy_Neg (Q^2<0). In contrast, AI-AI_Pos, Phy-AI_Neg, and Phy-AI_Pos had high predictive power (see Appendix).

5.4 Results

5.4.1 Descriptive Statistics

Table 8 shows the mean values and standard deviation of intention to use for each group. Further descriptive statistics for each group are presented in the Appendix.

	Group	**Mean Value**	**Standard Deviation**
Intention to use	Phy-Phy_Neg	4.399	0.614
	Phy-AI_Neg	4.110	0.659
	Phy-AI_Pos	4.130	0.750
	AI-AI_Neg	4.516	0.618
	AI-AI_Pos	4.508	0.610

Table 8: Mean values and standard deviation of intention to use for each group

5.4.2 Hypotheses Testing

Initially, 68.79% (n=432) of participants chose to have their MRI scans reviewed by a physician. After additional (positive or negative) information, 68.75% (n=297) chose to switch to the AI-based HIS. Participants who chose the AI-based HIS in the first decision (n=196), 97.45% (n=191) stuck with their decision despite the additional information. For this reason, switching behavior was only further investigated in Phy-AI. According to the results presented in Table 9, switching behavior decreased by 30.5% when positive information was provided, while switching behavior increased by 43.8% when negative information was provided. Therefore, we did not find evidence for H1a and H1b.

	B	Sig.	Exp(B)	95% C.I. for Exp(B)	
				Lower	Upper
Positive Information	-0.356	0.025	0.695	0.506	0.956
Negative Information	0.363	0.025	1.438	1.046	1.977

Table 9: Influence of positive and negative information on switching behavior

The mean values of intention to use was not significantly different between the groups. It was noteworthy that intention to use is highest for both AI-AI_Neg (4.516) and AI-AI_Pos (4.508) compared to the other decision options, regardless of framing (see Table 8). Then, using the integrated theoretical framework of Gesk et al. (2021), we calculated the results of the other hypotheses for each group. An overview of all path coefficients and effect sizes for each group is shown in Table 10.

	Negative Information			*Positive Information*	
	Physician → Physician	**Physician → AI**	**AI → AI**	**Physician → AI**	**AI → AI**
H2a: Perceived threats -> Fear (disease)	**0.406**** **(f^2=0.192)**	**0.368***** **(f^2=0.164)**	**0.463***** **(f^2=0.247)**	**0.221**** **(f^2=0.052)**	0.331** (f^2=0.116)
H2b: Perceived threats -> Intention to use	0.065 (f^2=0.006)	0.042 (f^2=0.003)	-0.120* (f^2=0.044)	-0.003 (f^2=0.000)	0.023 (f^2=0.001)
H3a: Non-adaptive rewards -> fear (disease)	0.024 (f^2=0.001)	**-0.385***** **(f^2=0.179)**	-0.116 (f^2=0.015)	**-0.401**** **(f^2=0.172)**	-0.185 (f^2=0.037)
H3b: Non-adaptive rewards -> Intention to use	-0.170 (f^2=0.043)	-0.113 (f^2=0.014)	-0.076 (f^2=0.015)	0.024 (f^2=0.001)	**-0.266*** **(f^2=0.091)**
H4: Fear (disease) -> Attitude (disease)	**0.303**** **(f^2=0.101)**	**0.434***** **(f^2=0.232)**	0.257** (f^2=0.070)	**0.427***** **(f^2=0.223)**	**0.267**** **(f^2=0.079)**
H5: Attitude (disease) -> Intention to use	0.238* (f^2=0.074)	0.187* (f^2=0.038)	**0.326***** **(f^2=0.261)**	0.052 (f^2=0.004)	-0.004 (f^2=0.000)
H6a: Perceived efficacy -> Fear (HIS)	-0.080 (f^2=0.006)	**-0.296***** **(f^2=0.096)**	**-0.403***** **(f^2=0.193)**	**-0.190**** **(f^2=0.034)**	-0.177* (f^2=0.030)
H6b: Perceived efficacy -> Attitude (HIS)	**0.386***** **(f^2=0.289)**	**0.602***** **(f^2=0.609)**	**0.528***** **(f^2=0.607)**	**0.517***** **(f^2=0.397)**	**0.424***** **(f^2=0.270)**
H6c: Perceived efficacy -> Intention	0.186 (f^2=0.038)	-0.101 (f^2=0.008)	0.107 (f^2=0.020)	0.140* (f^2=0.020)	**0.251***** **(f^2=0.070)**
H7: Fear (HIS) -> Attitude (HIS)	**-0.497***** **(f^2=0.532)**	-0.045 (f^2=0.003)	**-0.373***** **(f^2=0.303)**	-0.112* (f^2=0.020)	**-0.272**** **(f^2=0.121)**
H8: Attitude (HIS) -> Intention to use	**0.377**** **(f^2=0.163)**	**0.516***** **(f^2=0.224)**	**0.509***** **(f^2=0.366)**	**0.552***** **(f^2=0.308)**	**0.356**** **(f^2=0.130)**
H9a: Perceived norms -> Perceived threats	0.254* (f^2=0.069)	-0.006 (f^2=0.000)	0.096 (f^2=0.009)	0.090 (f^2=0.008)	0.142 (f^2=0.021)
H9b: Perceived norms -> Fear (disease)	0.167 (f^2=0.034)	-0.013 (f^2=0.000)	-0.145 (f^2=0.026)	-0.044 (f^2=0.002)	-0.055 (f^2=0.003)
H9c: Perceived norms -> Attitude (Disease)	0.182 (f^2=0.036)	0.061 (f^2=0.005)	0.088 (f^2=0.008)	-0.046 (f^2=0.003)	-0.168* (f^2=0.031)
H9d: Perceived norms -> Intention to use	-0.120 (f^2=0.018)	0.073 (f^2=0.007)	0.011 (f^2=0.000)	-0.001 (f^2=0.000)	0.020 (f^2=0.001)
H9e: Perceived norms -> Attitude (HIS)	**0.253**** **(f^2=0.124)**	**0.238***** **(f^2=0.105)**	0.143* (f^2=0.053)	**0.199**** **(f^2=0.059)**	**0.214*** **(f^2=0.071)**
H9f: Perceived norms -> Fear (HIS)	0.055 (f^2=0.003)	-0.014 (f^2=0.000)	-0.033 (f^2=0.001)	-0.167** (f^2=0.027)	-0.049 (f^2=0.002)
H9g: Perceived norms -> Perceived efficacy	**0.322**** **(f^2=0.115)**	0.084 (f^2=0.007)	0.081 (f^2=0.007)	**0.354***** **(f^2=0.143)**	**0.288**** **(f^2=0.091)**
H9h: Perceived norms -> Non-adaptive rewards	-0.003 (f^2=0.000)	0.060 (f^2=0.004)	0.136 (f^2=0.019)	0.059 (f^2=0.003)	0.032 (f^2=0.001)

Table 10: Path coefficients and effect sizes according to the hypotheses

Based on the results presented in Table 10, it can be seen that adaptive appraisals in medical decision-making had the greatest influence on intention to use in all groups. In Phy-Phy_Neg, attitude (HIS) was the only direct variable on intention to use. Perceived Norms and perceived efficacy had a positive effect on attitude (HIS), whereas fear (HIS) had a negative effect on attitude (HIS). Accordingly, our results supported H6b, H7, H8, H9e, and H9g and did not support H2a, H2b, H3a, H3b, H4, H5, H6a, H6c, H9a, H9b, H9c, H9d, H9f, H9h.

In Phy-AI_Neg, attitude (HIS) was also the only factor influencing intention to use HIS. A direct positive influence on attitude HIS was represented by perceived norms and perceived efficacy. For this reason, our results supported H6b, H8, and H9e. The results did not support H2a, H2b, H3a, H3b, H4, H5, H6a, H6c, H7, H9a, H9b, H9c, H9d, H9f, H9g, H9h.

In AI-AI_Neg, both attitude (HIS) and attitude (disease) directly influenced the intention to use HIS. Attitude (disease) was the only variable of the non-adaptive appraisals that influenced the intention to use. For the adaptive appraisals, attitude (HIS) was positively influenced by perceived efficacy and negatively influenced by fear (HIS). Therefore, our results supported H5, H6a, H6b, H7, and H8. For H2a, H2b, H3a, H3b, H4, H6c, H9a, H9b, H9c, H9d, H9e, H9f, H9g and H9h we could not find evidence.

For Phy-AI_Pos, again only attitude (HIS) had a positive direct influence on the intention to use HIS. Attitude (HIS) was again positively influenced by perceived norms and perceived efficacy. The non-adaptive appraisals had no further influence. Therefore, our results supported H6b, H8, H9e, and H9g and did not support H2a, H2b, H3a, H3b, H4, H5, H6a, H6c, H7, H9a, H9b, H9c, H9d, H9f, H9h.

In AI-AI_Pos, variables from adaptive and non-adaptive appraisals formed the intention to use HIS. Here, non-adaptive rewards had a direct negative influence on intention to use, whereas attitude (HIS) and perceived efficacy each had a direct positive influence on intention to use. Furthermore, attitude (HIS) was positively influenced by perceived norms and perceived efficacy and negatively influenced by fear (HIS). Perceived norms positively influenced perceived efficacy. Therefore, our results supported H3b, H6b, H6c, H7, H8, H9e, and H9g and did not support H2a, H2b, H3a, H4, H5, H6a, H9a, H9b, H9c, H9d, H9f, H9h.

Figure 12 shows all significant paths that directly or indirectly affect intention to use HIS.

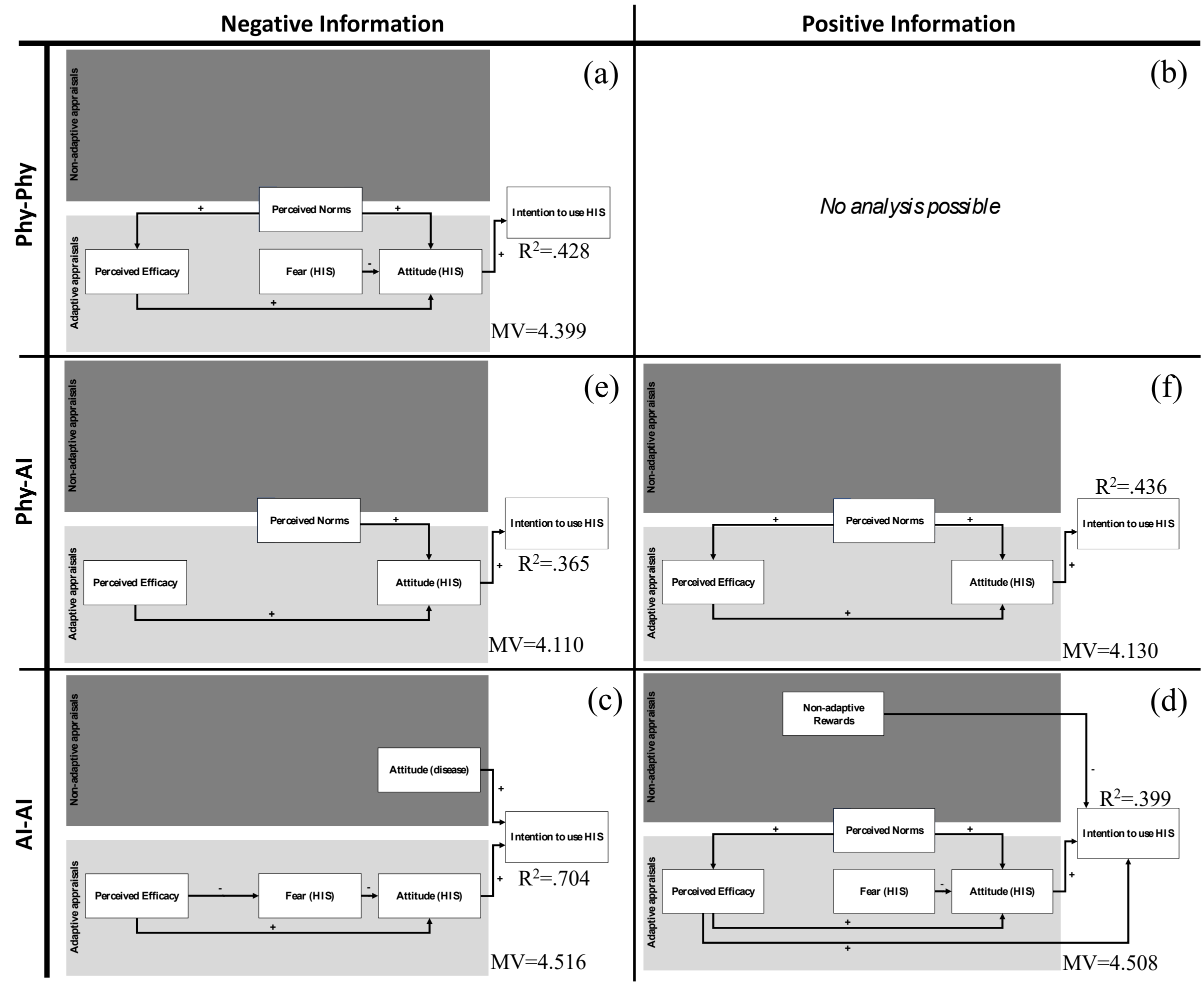

Figure 12: Results regarding hypotheses according to the scenarios (significant paths only)

5.5 Discussion

This study aimed to show how positive and negative framed information influences intention to use AI-based HIS for diagnostics. Here, individuals were given the option of choosing between an AI-based HIS and a physician to evaluate MRI scans. Although the AI-based HIS evaluated the MRI scans more accurately than the physician (Lennartz et al., 2021; Yokoi et al., 2021), a relatively large number of probands (n=135) chose the physician for the second decision. These results support the claim of Dietvorst et al. (2015) that individuals choose physicians despite the increased error proneness of physicians. Further, the findings support Logg et al. (2019) that individuals are also partially more likely to trust the assessment of an AI-based HIS than that of a physician.

However, the R^2 for Phy-Phy_Neg, Phy-AI_Neg, Phy-AI_Pos, and AI-AI_Pos according to Hair et al. (2019) can only be analyzed as weak. Only AI-AI_Neg has moderate explanatory power according to Hair et al. (2019). These results are much weaker than the R^2 classified as moderate to substantial in Gesk et al. (2021) and Gesk et al. (2022), who used the same integrated theoretical framework as in this study.

To answer the first research question, (RQ1a) the results show that for both positive and negative framed information, attitude (HIS) has a significant direct influence on intention to use. This is also independent of the diagnostic form chosen by the individual. This observation is also confirmed by the multimethod-multigroup comparison test according to Sarstedt et al. (2011) in connection with Hair et al. (2021). These results support the findings of Gesk et al. (2021) and Gesk et al. (2022) that attitudes (HIS) in different medical decision-making settings have a significant impact on intention to use HIS. In addition, the results confirm the findings of Zhang et al. (2021) that positive attitudes toward AI-based HIS are mediated by perceived efficacy and, ultimately, intention to use, among other factors.

Similarly, the results for both positive and negative framed information and for each decision type show that perceived norms have no direct effect on intention to use. However, it can be seen that perceived norms is an important indicator of other variables such as attitude toward HIS in decision-making in each decision type and in positive and negative framing except for AI-AI_Neg. Thus, perceived norms have an indirect influence on intention to use HIS. In contrast to the findings of Gesk et al. (2021) and Gesk et al. (2022), perceived norms do not directly influence intention to use HIS in this study. However, perceived norms are also important components of medical decision-making, as in Gesk et al. (2021) and Gesk et al. (2022).

Perceived efficacy is relevant in all decision processes. However, only for AI-AI_Pos perceived efficacy has a direct influence on the intention to use HIS. This differs significantly from the results for the other groups, where perceived efficacy has an indirect influence on intention to use. This is also shown by Gong et al. (2013), especially because the perceived efficacy of HIS has a direct impact on the intention to use HIS when it is positively framed.

Fear (HIS) is also an essential factor in medical decision-making. This fear of HIS can be for a variety of reasons. According to Aggarwal et al. (2023), care should be taken to ensure that HIS is personalized, provides a safe space for conversation, integrates with existing offerings, is an engaging experience, and is applicable to all populations.

The results of AI-AI_Neg show that in the case of negative framing, attitude (disease) has a direct positive influence on intention to use. However, the results of the path coefficients and the multimethod-multigroup analysis also show that attitude (disease) has no influence on positively framed decisions. These results differ from Gesk et al. (2021) and Gesk et al. (2022).

These studies also used the integrated theoretical framework used in this study, but show that setting (disease) is relevant, especially in situations with a physician, and becomes irrelevant when an AI-based HIS is part of the decision.

The non-adaptive rewards are only directly significant for AI-AI_Pos. However, a significant difference was found only for Phy-AI_Pos and AI-AI_Pos. The path coefficient analysis with the effect sizes show that perceived threats have either a direct nor indirect influence on the intention to use. Thus, the results contradict the findings of Gong et al. (2013) that perceived threat induced by framed information influences the intention to use.

To further answer the first research question, (RQ1b) the results showed that positive information had a weakly significant negative influence and negative information had a weakly significant positive influence on switching behavior. This supports the findings of Akl et al. (2011) that positively and negatively framed information (attribute framing) have either little or no difference in health behaviors at diagnosis. The weakly significant influences of positive and negative information on intention to use show that individuals weigh benefits and harms (see Resnik, 2004), especially in the case of negative framed information. Nevertheless, the influence of framed information is context dependent, as further studies show.

For answer the second research question, (RQ2) there is no clearly significant difference between diagnosis by a physician and diagnosis by an AI-based HIS. Therefore, there is no systematics as is the case in Gesk et al. (2021). Despite the unknown technology (AI-based HIS), individuals make their medical decision under similar aspects as in diagnosis by known procedures (physician). Furthermore, the average intention to use was highest among individuals who chose AI-based HIS twice. These findings therefore partially support Logg et al. (2019), who also found that individuals trust AI more than a human when making an assessment. Other research has shown that individuals would prefer the physician of an AI-based HIS (Longoni et al., 2019; Richardson et al., 2022; Yokoi et al., 2021). One possible explanation could be that in this study the AI-based HIS did not have close body contact with the patient. However, this contradicts the findings of Dietvorst et al. (2015) and Seitz et al. (2022), where the AI also acted as a prognosticator or diagnostic chatbot. Seitz et al. (2022) show that individuals still want to contact a physician when using telemedicine. Therefore, we suspect that medical decision-making is about the same for known diagnoses and new AI-based HIS when the patient does not contact the other actor. Another explanation could be that individuals had a free choice between options. It remains rather unrealistic that AI will replace the physician (Pesapane et al., 2018).

These findings can be applied to other contexts involving the individual's own body and its integrity (Say et al., 2006). One example is autonomous mobility in the form of autonomous driving cars (e.g., Cunneen et al., 2019; Ho, 2021). Here, the individual relinquishes responsibility for the integrity of his or her own body to the AI-based technology.

5.6 Conclusion

5.6.1 Theoretical Implications

Theoretical implications can be drawn from the results of this study. First, the application of the integrated theoretical framework of Gesk et al. (2021) is possible despite the different context. This provides a deeper understanding by focusing on adaptive and non-adaptive appraisals. When patients decide to use a diagnostic, the influence of attitudes (toward HIS) is critical to intention to use. Further, in decisions to use AI-based HIS, attitude (toward disease) (when framed negatively) and non-adaptive rewards (when framed positively) are important in addition to attitudes (toward HIS). However, it is not further apparent what influence framing has on medical decision-making.

Second, because negative information increases intention to use, framing in diagnostics is perceived similarly to decisions about treatments and new drugs.

Third, it becomes clear that patients' medical decision-making does not always focus on adaptive appraisals as the proportion of unknown HIS increases (see Gesk et al., 2021). In this study, it is even shown that variables from the non-adaptive appraisals have an impact on the intention to use HIS when AI-based HIS is chosen twice. In the other decision groups, no variables from the non-adaptive appraisals had an influence on the intention to use HIS.

5.6.2 Practical Implications

As AI-based HIS are likely to be implemented earlier in radiology diagnostics than in other medical fields (Pesapane et al., 2018), the results of this study have practical implications for implementation. First, physicians, clinics, and marketing agencies for medical HIS should contextualize the information to increase patients' intention to use it. In educational discussions about diagnostics, physicians and educational materials should emphasize the potential dangers of non-use.

Second, physicians, clinics, and marketing agencies for medical HIS should provide detailed explanations of the efficacy of the HIS. This is especially the case when the framing is positive in nature. In addition, fear of HIS is a key variable in medical decision-making, so agents should be transparent about fears and risks. Especially for AI-based HIS, the current European Commission guidelines on trustworthy AI should be followed (AI-HLEG, 2019).

5.6.3 Limitations and Future Research

As with any study, there are limitations to this research. First, intention to use has been used to determine the acceptability of AI-based HIS in diagnostics. It is important to note, however, that intention to use does not necessarily equate to use. Although intention to use is the most important predictor of actual use, individuals often deviate from their actual behavior despite having high intentions to use. This phenomenon is referred to as the intention-behavior gap (Fishbein & Ajzen, 2010). For this reason, it is useful to examine actual behavior in field experiments with positive and negative information.

Second, the scenario used in this study describes only the decision of whether the probands wants to be diagnosed by a human physician or an AI-based HIS. We manipulated the decision with positively and negatively framed information based on actual outcomes (see Rauschecker et al., 2020). Unfortunately, to date there are no studies of the objective success probabilities of the AI-based HIS and the human physician in near-body treatments. Therefore, future research can investigate what outcomes occur when the AI-based HIS perform an actual body-based treatment, such as surgery.

Third, the ability to make free choices may have an impact on decision-making and the ultimate intention of use. To make a more accurate statement, different options need to be tested.

Forth, our results show an inadequate prediction in some of the groups, which is why the validity of this study is not given, or only partially given, in the groups in question. Furthermore, the multimethod-multigroup analysis might have been influenced by a different group size (see Hair et al., 2021). In order to avoid the family-wise error, we have already performed all available multigroup analyses. For this reason, further research may yield different results. Further, the results of AI-Phy_Pos and AI-Phy_Neg could not be analyzed due to the small sample size resulting from the free choice. Also, the data of the Phy-Phy_Pos group could not be analyzed. Therefore, this study does not yet provide a complete picture of medical decision-making with positively and negatively framed information for AI-based HIS in diagnostics. Further research should help to fill this knowledge gap in other contexts.

Fifth, according to several studies, this is an important factor (e.g., Yun et al., 2021). In this study, the empathy factor was explicitly not focused in order to determine which other factors have an influence in medical decision-making with regard to intention to use. However, empathy may be (1) the missing link to intention to use in Phy-Phy_Pos and (2) the crucial difference of framed information on intention to use AI-based HIS. Further, empathy is probably more important in body-related services than in diagnosis. Further investigations are still necessary here.

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5.8 Appendix

The questionnaire, the data as well as the detailed results of the analyses can be found here:

Gesk, T. S. (2023, March 3). Framed Information in Medical Decisions for AI-based HIS: Balance between Adaptive and Non-Adaptive Appraisals. https://osf.io/jt6sc/?view_only=d51f82a7abca4187a92855dbebe4fe34

Eidesstattliche Versicherung

Ich erkläre hiermit, dass ich die vorliegende Arbeit ohne unzulässige Hilfe Dritter und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe; die aus fremden Quellen direkt oder indirekt übernommenen Gedanken sind als solche kenntlich gemacht.

Die Arbeit wurde bisher weder im Inland noch im Ausland in gleicher oder ähnlicher Form einer Prüfungsbehörde zur Erlangung eines akademischen Grades vorgelegt.

Rostock, 13.03.2023

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Tanja Sophie Gesk

Eidesstattliche Versicherung

Ich erkläre hiermit, dass keine nicht bestandenen früheren Promotionsversuche vorliegen.

Rostock, 13.03.2023

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Tanja Sophie Gesk