The Effect of Trust in Technology on the Intention to Adopt Mobile Health Apps and the Mediating Effect of Perceived Risk

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ABSTRACT

The digital transformation of healthcare has spawned technological innovations, including mHealth, which can reduce costs and improve the efficiency of healthcare systems. However, the adoption and implementation have been slower than expected due to various barriers, including end-user resistance. Researchers have found that using health-related mobile applications is below average in Germany compared to the global average. This study investigates the influence of trust and perceived risk on the adoption of mobile health apps in Germany.

A simple model was created from literature insights and broken down into testable hypotheses. A quantitative research method using a survey to collect data from 197 participants in Germany was used. Hypotheses were tested using mediation analysis.

Trust in technology is positively related to the intention to adopt and is negatively related to perceived risk. Results show no evidence of a significant relationship between perceived risk and intention to adopt. No mediation effect was found, possibly due to the measurement scales or sample characteristics. Functionality was identified as a key trust increaser and human-related factors such as data accuracy and integrity as trust reducers. Data security and privacy concerns were identified and highlighted the need for greater transparency in using personal health data in the mHealth context.

This study provides insights into the factors contributing to the slow adoption of mobile health apps in Germany and highlights the importance of trust and perceived risk in technology adoption. Important implications can be extracted for health app providers, regulators, and policymakers.

Keywords: mHealth, Mobile Health Apps, Adoption Intention, Trust, Trust in Technology, Perceived Risk

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SUMÁRIO

A transformação digital na saúde tem envolvido diversas inovações incluindo a área da saúde móvel. No entanto, a adoção tem sido mais lenta do que o esperado devido a vários obstáculos, incluindo a resistência dos utilizadores finais. A utilização de aplicações moveis na área de saúde na Alemanha tem sido identificada como inferior à média na União Europeia. Este estudo investiga a influência da confiança e da perceção de risco na adoção de aplicações móveis de saúde na Alemanha.

Um modelo simplificado foi criado com base na literatura recolhida incluindo um conjunto de hipóteses. Foi utilizado um método de investigação quantitativo que utilizou um inquérito para recolher dados de 197 participantes na Alemanha. As hipóteses foram testadas através de análises de mediação.

A confiança na tecnologia tem um impacto positivo na intenção de adoção e um impacto negativo na perceção de risco. Não houve evidência de um efeito significativo entre o risco percebido e a intenção de adoção. Não foi encontrado qualquer efeito de mediação. A funcionalidade foi identificada como um fator-chave para aumentar a confiança e os fatores humanos, ou a integridade dos dados como capazes de contribuir para a sua redução.

Este estudo fornece informações sobre os fatores que contribuem para a lenta adoção de aplicações móveis de saúde na Alemanha e destaca a importância da confiança e da perceção de risco na adoção de tecnologias. As conclusões deste estudo têm implicações importantes para os fornecedores de aplicações de saúde e para os responsáveis pelas políticas públicas.

Palavras-chave: mHealth, Aplicações móveis de saúde, Intenção de adopção, Confiança, Confiança na tecnologia, Risco percebido

Título: O Efeito da Confiança na Tecnologia na Intenção de Adopção de Aplicações Móveis de Saúde e o Efeito Mediador do Risco Apercebido

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LIST OF ABBREVIATIONS

mHealth = Mobile Health

eHealth = Electronic Health

EHR = Electronic Health Record

DiGA = Digitale Gesundheitsanwendung (Digital Health Application)

EHCR = Electronic Health Care Records

TAM = Technology Acceptance Model

PDA = Personal Digital Assistant

IS = Information Systems

CHAPTER 1: INTRODUCTION

1.1 Background

According to estimates by the European Commission, one in every three Europeans will be above 60 by 2060 (European Commission, 2019). The global trend of population aging will imply extensive social, economic, and political consequences. Pressure is put on the healthcare system due to the constantly rising demand for higher-quality services (Weck & Afanassieva, 2023).

The digital transformation of businesses and organizations has visibly impacted all industries. The healthcare sector has experienced a significant digital transformation owing to various promising technologies, with a plethora of new technological innovations emerging in recent years. Digitally-driven technological transformations can be seen in diagnostics, healthcare administration, management, equipment, and delivery. One of the technological innovations that substantially enhanced the diagnosis, treatment, and management of diseases is mobile health, also referred to as mHealth (Iyanna et al., 2022). mHealth can potentially reduce costs and improve the effectiveness and efficiency of healthcare systems worldwide, particularly in light of increasing costs in healthcare and shifting demographics (Uncovska et al., 2023).

Despite digitalization's significant advantages, this transformation has encountered numerous obstacles. While mHealth has demonstrated considerable potential and a positive impact on the healthcare sector, its adoption and implementation have been slower than anticipated. Past research reported the resistance to adopting technology-driven innovations as a significant hindrance to achieving a successful digital transformation of the healthcare sector (Iyanna et al., 2022). The acceptance and widespread adoption of mHealth is considered vital to its effectiveness and economics (Heidel & Hagist, 2020).

Scholars found that using mHealth and health-related mobile applications is below average in Germany (Hannemann et al., 2021). A GfK survey across 16 countries found that the average health and fitness app use is 33% (Herder, 2016). Only 28% of individuals in Germany who have access to the Internet use mobile health apps to manage their health. Of those who had experimented with using them, 13% discontinued it after some point. Only a small proportion of people use them to manage their health. Most users use administrative mobile health apps, e.g., for booking online appointments (Hannemann et al., 2021).

In October 2019, the DVG was enacted in Germany, marking an important milestone in the German healthcare system (Stern et al., 2020). This law introduced a German healthcare reimbursement system known as DiGA. The DVG gives more than 73 million people with statutory health insurance access to these digital tools (Schliess et al., 2022). DiGAs are classified under European regulations as medical devices designed to monitor, treat or mitigate the effects of various diseases (Heidel & Hagist, 2020). Despite potential benefits, there are barriers to their widespread adoption. These challenges include physician skepticism, prescribing processes and reimbursement, the need for transparent quality assurance and clinical evidence, and their effectiveness (Schliess et al., 2022). To ensure clarity, it is important to distinguish between two uses of the term “DiGA”. This study will use the term “DiGA(s)” to refer to health apps considered as a DiGA. The term “DiGA Act” has been popularized to denote the DVG law.

Resistance to adoption is a human response explained by many factors. Past research sought to explore the sources of individual differences in the resistance to digital health technologies (Iyanna et al., 2022). Some studies found positive attitude, perceived usefulness, and the expectation of benefits of mHealth to be critical predictors of adoption (Dahlhausen et al., 2021). Various scholars also found what has been called 'human factors' as key to successfully implementing digital health technologies (Saliba et al., 2012).

Trust is considered one of the most critical determinants of adopting technology and digital services (Weck & Afanassieva, 2023). The success of digital health is dependent on trust from patients, administrators, and professional end users. However, the so-called 'building blocks' of trust in digital health systems have been inadequately explored. Hence, it is valuable to understand the determinants of trust in digital health (Adjekum et al., 2018). Patient trust in health professionals involved with digital health technologies has only been explored in a few studies (Saliba et al., 2012). The influence of initial trust in adoption behavior has rarely been explored (Cao et al., 2020), and the role of trust in the health context still needs to be determined (Fox & Connolly, 2018). While all potential barriers to adopting mobile health apps are worthy of examination, this study focuses specifically on trust. Scholars agree that it is crucial to investigate how trust in digital health technologies can be increased (Korn et al., 2022).

Past research identified **perceived risk** as another important factor for eHealth (Schnall et al., 2017) and a significant barrier to technology adoption (Hasan et al., 2021). Perceived risk has been defined as "the degree of uncertainty related to using the medium" (Schnall et al., 2017, p. 3). eHealth users are mainly concerned about the security and privacy of personal health information (Fox & Connolly, 2018; Schnall et al., 2017). The relationship between trust and risk has received extensive research attention (Hsieh, 2015; Mou et al., 2017). However, so far as we know, the relationship between trust in technology and perceived risk in relation to the adoption intention of mobile health apps has not been previously studied.

1.2 Problem Statement

Despite the potential benefits of mobile health apps for improving patient outcomes and the DiGA Act, their adoption rates in Germany have been relatively low (Dahlhausen et al., 2021; Hannemann et al., 2021; Heidel & Hagist, 2020). One possible explanation is that perceived risks associated with mobile health apps may deter individuals from adopting them, even if they trust the technology (e.g., (Fox & Connolly, 2018; Rauer, 2012; Uncovska et al., 2023). This study aims to investigate the relationship between trust in technology, perceived risk, and the intention to adopt mobile health apps and to understand the role of perceived risk as a mediating factor in this relationship.

The main research question and sub-research questions are:

Research question: How does trust in technology influence the intention to adopt mobile health apps among individuals in Germany, and does perceived risk mediate this effect?

Sub-research questions:

What factors influence trust in mobile health apps?

What are the perceived risks associated with mobile health apps?

1.3 Relevance

Academic research in this subject field has been relatively scarce, although the recent COVID-19 pandemic has caused a notable increase in the use of digital health technologies and eHealth solutions and attention to the importance of digital transformation in the healthcare sector, including by researchers. (Iyanna et al., 2022). However, even though the potential of digital health technologies has become apparent during the pandemic period (Hannemann et al., 2021), this increase has not persisted (Iyanna et al., 2022). Researchers found a re-emergence of resistance among practitioners toward using digital health technologies (Iyanna et al., 2022).

While there has been extensive research on physicians' adoption of mobile health apps, there is a lacuna regarding factors determining individuals' adoption (Cho et al., 2014).

Most previous studies examined the resistance to adoption, focusing on specific innovations such as EHRs. Limiting research to only a few specific technologies is restrictive (Iyanna et al., 2022). The factors that influence adoption vary depending on the specific technology used. Therefore, it is important to study different digital health technologies independently. Empirical analyses of the determinants of mHealth adoption remain limited (Fox & Connolly, 2018).

This study aims to make a valuable contribution to the field by deepening our understanding of adoption resistance, with a focus on mobile health apps. Although the adoption of mHealth technologies in Germany received some attention, it has not been the subject of much previous research (Vayena et al., 2018). A single-country focus allows the inference of specific recommendations to facilitate the adoption of mobile health apps in Germany. Although a global phenomenon, digital health is adopted and implemented differently around the world (Vayena et al., 2018). However, important insights from a large country can contribute to global knowledge in this field.

While much evidence exists on the importance of perceived risk, the nature of the relationship between trust, risk, and acceptance remains controversial (Zhang, 2014). Trust and risk perception are considered among the most important psychological states affecting online behavior. Although many empirical studies investigated the impact of trust and risk perceptions of acceptance of e-services, the subject field remains fragmented since the literature is characterized by opposing views. This led to a more complex number of research models being established. In addition, the association between trust and risk has been studied extensively, but the direction of causality remains controversial among scholars (Mou et al., 2017). Hence, further research is needed to clarify the role of trust and risk perceptions (Hsieh, 2015). The present study will predominantly enrich the subject field by investigating the relationship between the two variables and examining perceived risk as a mediating variable in the relationship between trust in technology and intention to adopt.

1.4 Research Methods

This thesis applies a quantitative, transversal descriptive approach to examining literature. It starts with desk research of academic literature to build a theoretical model for hypotheses generation. It then analyzes data and tests hypotheses based on primary data collected through a survey method.

1.5 Dissertation Outline

The outline of this study will be as follows. First, the introduction provides a brief background and rationale for the study and states the relevance and research methods used. Second, this study includes a theoretical background of the main constructs before proposing hypotheses that will be tested empirically and further discussed in view of collected literature. Methodology used in this study is outlined in Chapter 3. Chapter 4 presents empirical results, including the analyses of the relationships between theoretical constructs, verifying the corresponding hypotheses. The discussion chapter interprets findings in light of prior research and explains their possible explanations. This will support understanding the relationships of the main variables proposed in this study. It also includes the limitations and suggestions for future research. The final part of this study is the conclusion of the main findings.

CHAPTER 2: THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

This chapter presents the theoretical background for the main concepts related to the research questions and the purpose of this study. The subjects were examined using prior studies and supporting empirical evidence from numerous academic journals. Based on the findings in the literature, hypotheses will be formulated.

2.1 Mobile Health Apps

Mobile health apps are a subset of mHealth. Numerous definitions for mHealth exist. Scholars defined mHealth as “the use of mobile devices, such as mobile phones, tablet computers, and PDAs, to provide medicine, public health, and health services” (Song & Yu, 2019, p. 1). It includes numerous mobile applications, health record systems, and wearable devices (Fox & Connolly, 2018). mHealth is a subset of eHealth applications and supports self-management of healthcare by using mobile devices and mobile health apps to monitor, measure, and analyze health-related data. mHealth technologies are used, for example, for individual health promotion, diagnosis and treatment of diseases, support lifestyle changes, and higher efficiency in health care in resource-poor regions (Hannemann et al., 2021). It can serve as a decision-making aid about health by the provision of round-the-clock real-time feedback and gives consumers the possibility to learn about and manage their health (Schnall et al., 2017).

This study focuses specifically on mobile health apps. Mobile devices have several sensors that can be used to measure and track vital parameters and other health-related data. Mobile health apps are then able to analyze and process health data. They are a fairly new phenomenon. The extent to which they are being utilized is still unclear. So far, there is only slight evidence of the actual benefits. There are several risks associated with possible side effects, or simply failure to obtain the desired results which have been identified (Rasche et al., 2018).

For this study, the working definition of mobile health app is the one suggested by Anderson et al. (2016, p. 1), who defined it as “any commercially-available health or fitness app with capacity for self-monitoring.” While various mobile health apps have been designed to support health professionals, only a small number received regulatory approval. In 2022, more than 325,000 were counted across commercial app stores of mobile platforms (Grundy, 2022).

Mobile Health App Adoption in Germany

In 2019, a survey in Germany by Bitkom Research showed that out of 792 participants who own smartphones, over 60% already use mobile health apps. In 2020, this survey was repeated and showed that this rate increased to 75%. However, these include mainly apps for fitness and health exercises, learning apps for topics like stress reduction, and apps for recording vital functions such as heart rate (Schudt et al., 2022). Approximately 28% of German individuals track at least one health parameter (Heidel & Hagist, 2020). The usage rate of mobile health apps that manage diseases is low. The general willingness among individuals in Germany to use mobile health apps/DiGAs is approximately 76%, especially if they are governmentally certified. However, a study found that only 27% of respondents were willing to pay out of pocket (Uncovska et al., 2023).

By 2050, 50% of the German population will be older than 50 years. Limited mobility, autonomy, and diseases often go hand-in-hand with old age. Hence, it is essential to provide, in particular, older adults with mobile health apps which cover a range of diseases and other topics like fall risk. A study found that most users of mHealth in Germany are between the ages of 30 and 50, with endocrine or mental health conditions (Uncovska et al., 2023). Results of previous studies show that older German adults are more likely to use mobile health apps the lower their age and the higher their level of technical readiness (Rasche et al., 2018). Other studies agree that most health app users are young and highly educated and perceive themselves to be in good health (Cho et al., 2014; Heidel & Hagist, 2020).

DiGA

The recent COVID-19 pandemic emphasized the need for digital tools to support worldwide patient monitoring and care delivery. In October 2019, Germany's parliament passed the DVG (Stern et al., 2020). It became the first country in the world to introduce a digital care act as an incentive system to improve the use of mobile health apps and wearables among its population (Dahlhausen et al., 2021; Heidel & Hagist, 2020). The act introduces a fast-track pathway for mobile health apps/DiGAs into the German statutory health care system. It is one of the most progressive "pilot" projects in the history of the German healthcare system. This act allows physicians to prescribe statutory financed and certified mobile health apps and wearables to patients (Heidel & Hagist, 2020). The fast track enables over 73 million people insured under the German statutory health insurance system to receive a prescription for DiGAs (Schliess et al., 2022).

Until now, there is no clear differentiation between DiGAs and other mobile health apps (Uncovska et al., 2023). The German Ministry of Health explains the concept of DiGA as “a medical device within the scope of the European medical device regulation and classified as risk level I and not higher than a risk level IIa” (Heidel & Hagist, 2020, p. 2). DiGA is a portable technology with the potential to monitor, treat or reduce the effects of diseases (Heidel & Hagist, 2020). The expected patient demand and acceptance of the DiGA Act is a topic of current interest among researchers in Germany (Heidel & Hagist, 2020).

However, despite the advantages of the DiGA Act, there are also some barriers to adopting DiGAs (Schliess et al., 2022). For example, there are hurdles to a permanent prescription and reimbursement. Only a few have achieved this status. Also, many physicians are skeptical about them. Prescription rates have been lower than anticipated (Schliess et al., 2022). So far, DiGAs are limited to only a few medical specialties, such as diabetes and psychotherapy, which may be another cause for its slow adoption (Dahlhausen et al., 2021). Most DiGAs are also considered complementary and not a substitute for established therapies. Without transparent quality assurance and clinical proof of beneficial healthcare, the effect causes further stakeholder skepticism. Health insurance companies criticize the high costs, while manufacturers criticize the demanding and resource-intensive preparation of the fast-track application (Schliess et al., 2022).

2.2 Trust in Technology

Trust is a critical factor in adopting mobile health apps, given the sensitive nature of health-related data and the uncertainty involved (Mcknight et al., 2011).

It is a multifaceted construct that is not easily definable in operational terms (Adjekum et al., 2018). Even though the importance of trust has been widely recognized, there is no consensus on the definition of trust in literature (Dimitrakos, 2002). Scholars have previously referred to trust as the “expectations about positive motives” (Das & Teng, 1998, p. 494) or the expectation that a partner does not act in self-interest (Das & Teng, 1998). Numerous scholars describe trust as “the expectation that an actor can be relied on to fulfill obligations, will behave in a predictable manner, and will act and negotiate fairly when the possibility for opportunism is present” (Zaheer et al., 1998, p. 143).

Most past literature examined and defined trust in regards to *trust in people* regardless of *trust in technology* (Pavlou, 2003). It appears more natural to trust a person than a technology (Mcknight et al., 2011). According to Friedman et al. (2000, p. 36), “People trust people, not technology.” Internet research shows that trust in another actor (e.g., app provider) rather than the technology itself influences an individuals’ decision to use technology. Comparatively little research on trust in technology exists. However, several researchers argue against this extreme position that people trust people and not technology and created new definitions and constructs for trust in technology (Mcknight et al., 2011).

It is still an open question in academic literature whether it is appropriate to discuss trust between people and inanimate objects like technological products (Adjekum et al., 2018). However, empirical evidence suggests that individuals do not perceive trust-related concepts differently, whether the relationship is solely between humans or between humans and technological products (Weck & Afanassieva, 2023). Technology lacks moral agency. Hence, technology-related trust reflects perceptions about the characteristics of technology instead of its will or motives (Mcknight et al., 2011).

Trust in technology has been described as the belief that in any situation with the possibility of a negative outcome, this specific technology has the attributes needed to function as expected (Mcknight et al., 2011; Weck & Afanassieva, 2023). This definition will be adopted as the working definition of trust in technology for the purpose of this study. Trust in technology is a viable concept if an individual can depend on the technology’s attributes under uncertainty. For example, an individual might trust Blackberry’s email system to send messages correctly. Hence, trust in technology involves accepting the vulnerability that the technology may or may not successfully complete the task and fulfill the expected responsibilities. Regardless of why technology may have failed, the user accepts the risk of incurring negative consequences (Mcknight et al., 2011).

Technology adoption can be described as a process that begins with the potential user becoming aware of the technology and ends with the user utilizing and embracing the technology. Hence, an individual decides to use or reject the technology (Weck & Afanassieva, 2023). Numerous factors can affect an individual’s decision to adopt or reject the technology.

Mobile health apps may be required to abide by specific criteria to prove trustworthiness. Mcknight et al. (2011) suggest three attributes that users expect a technology to have. The first attribute is *functionality*, meaning the user decides whether the technology functions as expected and has the features necessary to complete the task. Second, while technology has no moral agency and cannot care for its users, users expect technology to contain a help function. The level of *helpfulness* of technology is important since users might have differing opinions on how helpful the advice is to complete a task. Hence, individuals have greater trust in technology when the technology provides practical help. Third, users expect technology to be *consistent, predictable* (e.g., printing on command), and *reliable*.

Moreover, past literature identified a number of factors affecting trust in the context of digital health technologies, as well as factors that hinder the adoption of mobile health apps in general. Trust enablers are those factors that promote individuals' trust in digital health, while trust impediments describe those factors which may impede trust. These factors influence an individual's decision to trust digital health technologies (Adjekum et al., 2018). The determinants of trust in digital health technologies remain underexplored. Thus, it is paramount to investigate the determinants of trust in this context (Adjekum et al., 2018).

Previous studies found that a lack of trust in data security is one of the main reasons for people not to use mobile health apps (Dahlhausen et al., 2021; Heidel & Hagist, 2020). The lack of trust is mainly caused by missing transparency. Full transparency about data processing may be one of the leading solutions to data privacy concerns. More specifically, transparency about ownership and data control are essential elements of trust. Other elements of trust are accountability and benefit sharing (Vayena et al., 2018). However, some of these factors focus mainly on trust in people since elements like accountability and missing transparency are caused by humans. As described earlier, this paper focuses on the trust relationship between humans and technology.

A short summary of trust-related literature can be viewed in Appendix 1.

Based on the previous discussion, it is hypothesized that:

Hypothesis 1. The higher (lower) the level of trust in technology, the higher (lower) the intention to adopt mobile health apps.

2.3 The Mediating Effect of Perceived Risk

Trust and risk are crucial elements of any technology-driven product due to the high level of uncertainty involved. The impersonal and distant nature of the online environment render risk.

E-commerce literature found two forms of uncertainty present in online transactions, which can be adopted for the purpose of this study. These forms of uncertainty are behavioral uncertainty and environmental uncertainty (Pavlou, 2003).

Risks are either technology-driven (environmental risk) or relational (behavioral risk). Behavioral uncertainty arises when an actor (e.g., app provider) has the chance to act in an opportunistic manner by taking advantage of the impersonal and distant nature of the online environment. *Behavioral uncertainty* may include economic risk (monetary losses), personal risk (unsafe products/services), performance risk (imperfect monitoring, e.g., by physician or app provider), and privacy risk (opportunity to disclose private data). *Environmental uncertainty* stems from the uncertainty of the Internet, which includes private data breaches and the stealing of personal information by hackers. The types of risk involved with environmental uncertainty are economic risk (monetary losses) and privacy risk (possibility of a data security breach). These proposed types of uncertainty should be jointly considered because an individual has an overall expectation regarding the behavior of the actors involved and the ability of the technology to function as expected when considering the adoption of a specific technology (Pavlou, 2003).

mHealth offers its services through an open network vulnerable to information/network security breaches (Shareef et al., 2014). Hence, using mHealth technology gives rise to privacy and security concerns among individuals associated with an increasing threat landscape (Fox & Connolly, 2018; Shareef et al., 2014). Patients using mHealth continuously disclose sensitive personal health data and personal identification information to networks (Shareef et al., 2014). Especially in Germany, data privacy and security concerns are strong (Heidel & Hagist, 2020). The danger of misinformation is a serious concern in digital health applications, potentially leading to incorrect treatments and misdiagnosis (Schudt et al., 2022).

For the purpose of this study, environmental uncertainty can be adapted to the environmental uncertainty that stems from the uncertainty of health app technology. Cyber and information breaches, including stealing personal information, are risks in any online environment, including app technology. Risks specific to mobile health app technology are risks caused by the technology itself, such as faulty alarms, errors, malfunctioning, and the risk that the patient is presented with incorrect or incomplete information (Akbar et al., 2020).

Previous authors hypothesized that risk and trust contribute to the intention to use mHealth technology (Schnall et al., 2017). While some scholars argue that unforeseen circumstances or events drive trust, others suggest that risk is driven by the power to weigh risks and choose between actions. Although the possibility of deception within a trust relationship exists, whether an individual decides to trust solely based on risk assessment or by actively evaluating alternative options (Adjekum et al., 2018) remains uncertain. It is assumed that trust can be established if the risks and uncertainties associated with their usage can be reduced to a minimum (Adjekum et al., 2018).

For these reasons, a second hypothesis is worth considering:

Hypothesis 2. The higher (lower) the trust in technology, the lower (higher) the perceived risk involved with using the technology.

Risk is perceived due to the possibility of suffering a loss while using technology. In particular, individuals perceive risk if the security and privacy of personal health information is unverified. A previous study found that individuals show concern over the risk of who can access their personal health information and where the information will be stored. Individuals' risk perception is negatively related to the intention to transact. Hence, individuals are less likely to use mobile health apps if the perceived risk of the disclosure of personal health information is high. If patients are unwilling to use mHealth technology due to security concerns or other involved risks, adoption will fail, and mHealth will be unable to improve health outcomes for patients (Schnall et al., 2017).

Hence, it can be hypothesized that:

Hypothesis 3. A lower (higher) level of perceived risk leads to a higher (lower) intention to adopt mobile health apps.

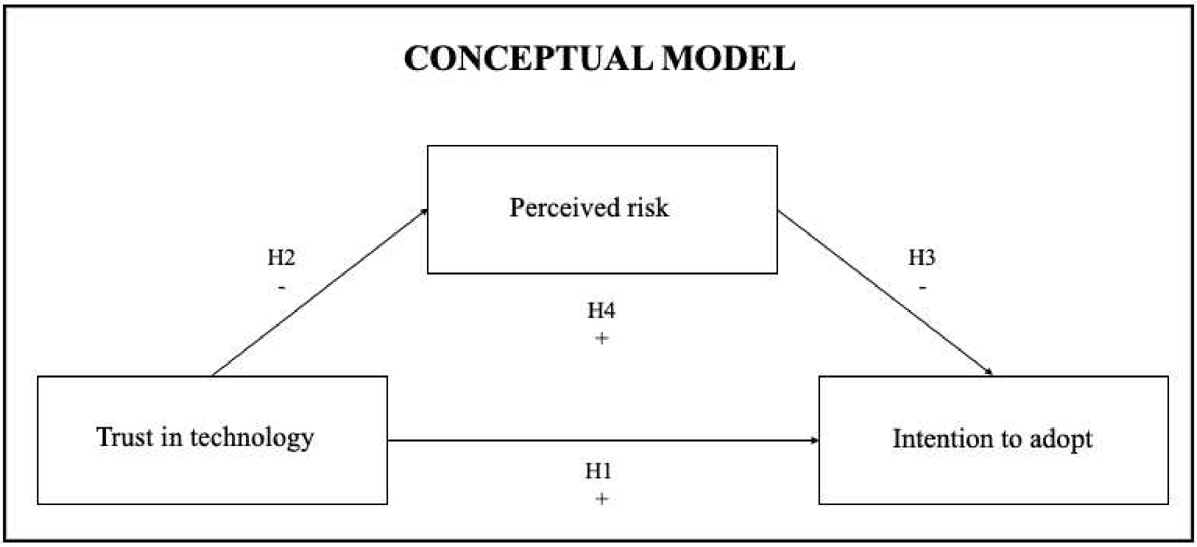
Therefore, the direct and indirect effect of perceived risk on the intention to adopt mobile health apps is hypothesized as follows:

Hypothesis 4. Perceived risk mediates the relationship between trust in technology and the intention to adopt mobile health apps.

2.4 Summary of the Conceptual Model

Based on the research questions and formulated hypotheses, a conceptual model is proposed, represented in Figure 1. The model includes the independent, dependent, and mediating variables and the expected relationships between these variables. The relationship between trust in technology and the intention to adopt is expected to be positive (H1). If individuals trust in technology, their intention to adopt is expected to be high. The relationship between trust in technology and perceived risk is negative (H2). It is expected that when individuals show higher trust in the technology, the level of perceived risk is lower. Similarly, if the level of perceived risk is lower, the intention to adopt is higher. Hence, the relationship between perceived risk and intention to adopt is expected to be negative (H3). Lastly, the relationship between trust in technology and intention to adopt is expected to be strengthened by a low level of perceived risk because the less risk people perceive with using technology, the more trust they have; therefore, they have a higher intention to adopt (H4).

Figure 1: Conceptual Model – TRIAM – Trust, Risk, and Intention to Adoption mHealth



CHAPTER 3: METHODOLOGY

The purpose of this chapter is to describe the methods and techniques used to examine the hypotheses proposed in Chapter 2. First, the motivation for choosing the selected research design will be presented. After that, the chapter outlines the measurement constructs and scales.

Last, the data collection procedure, the data preparation steps, and the plan for data analysis will be discussed.

3.1 Research Design

The research design for this study is a descriptive research design analyzed through quantitative methods. It includes a theoretical discussion based on literature insights into the main topics and a survey method. The literature insights facilitated the creation of a simple model, which has been broken down into testable hypotheses. The survey method allows the collection of primary data and the testing of hypotheses. A cross-sectional survey design is employed, meaning that data is collected at a single point in time. It is to note that findings offer insights into the relationships between the variables but not about causality. A longitudinal survey design is needed to discuss causal directions, which would go beyond the time frame of this study (Rindfleisch et al., 2008). A descriptive research design allows specific insights into the subject field (Creswell, 2014). This method is useful, as prior research exists on the impact of trust on the adoption of digital health technologies. However, more research is needed on specific determinants and factors affecting this relationship.

The objective of this study is to examine the relationship between trust in technology, perceived risk, and the intention to adopt and to understand the role of perceived risk as a mediating factor in this relationship. To do this, it is important to examine the factors influencing trust in technology. In addition, the perceived risk associated with trust and adoption, and more generally, technology need to be understood.

A theoretical background builds the foundation of the study by providing an understanding of the main topics under research. It defines and explains the primary constructs, includes a review, and gives credit to existing studies. It also identifies gaps and open questions left from previous research, which helps to identify the need for additional research. It mainly builds the line of argumentation for the relationships of the variables and, thus, creates the foundation for the proposed hypotheses. Quantitative research requires a hypothesis before the start of the investigation (Hemachandra, n.d.). This study uses directional hypotheses, meaning the hypotheses proposed are predicted based on prior literature and studies (Creswell, 2014), outlined in Chapter 2.

There are several advantages and disadvantages to using a quantitative research design for this study. The measurement scales used for the main variables in this study have been adapted from numerous validated measurements. Since trust is an exceptionally widely researched phenomenon, numerous studies use quantitative and/or qualitative methods. Many previous studies used 7-point Likert scales to measure trust, perceived risk, and intention to adopt. Likert scales usually provide a very high level of precision in capturing the feelings and opinions of individuals (Munshi, 2014). Both constructs, trust and perceived risk, are captured by seven items each on the questionnaire, which allows for capturing nuanced variations of trust and risk levels among individuals.

A quantitative measurement presents numerical data, allowing statistical analysis. Descriptive statistics, hypothesis testing, correlation analysis, and regression modeling enable exploring the relationship between all three variables of interest. Hence, quantitative measurements allow for numerical representation, simplifying replication and verification of results. However, by using a quantitative measure, a complex construct like trust is reduced to seven items. A qualitative measurement would allow us to capture a more comprehensive understanding of the perspectives and feelings of individuals for trusting in technology and why individuals perceive risk. However, qualitative methods can limit generalizability since findings are specific to a relatively small sample. Also, it limits the ability to measure and quantify the relationships between the variables of interest (Queirós et al., 2017). If time and resources allow it, it would be best to combine both approaches.

The structure of the survey was as follows. First, participants were presented with an introduction text, including an explanation of the aim of this survey, a brief definition, and five examples of commonly used mobile health apps in Germany. After agreeing to the consent form, participants were led to the start of the study. The first two questions were control questions. If participants marked either of these questions with “no,” they were automatically sent to the end of the study. This was followed by three enthusiasm check questions. Following, questions of the three main topics were asked with 17 items. Towards the end of the study, an attention check question was asked to catch respondents who may have been mindlessly clicking through the survey. Responses of participants who failed this attention check question have been excluded from the sample. The survey ended with questions on demographics. The survey protocol is shown in Appendix 3.

Measurement Constructs

To investigate the relationships between the variables, this study considered a correlational design. The measurement instruments to measure the constructs under study have been adapted from existing measurement scales from past studies. Thereby, construct validity and reliability can be ensured to a high degree. A 7-point Likert scale was used to measure all items which measure the primary constructs of the present study. The 7-point Likert scale ensures greater variation compared to the 5-point Likert scale (Hasan et al., 2021).

The three variables of interest were measured on a 7-point Likert scale ranging from (*1 = Strongly disagree to 7 = Strongly agree*").

Four control variables were included to enhance the validity of the study and ensure unbiased results. These variables include 'Age,' 'Gender', 'Education,' and 'Yearly Income (in Euro €).' This study controls for age and education because previous studies suggested that most health app users are young and highly educated (Cho et al., 2014; Heidel & Hagist, 2020; Rasche et al., 2018). Cho et al. (2014) also found that mobile health apps are most popular among females. Further, health literacy has often been found to influence health app adoption. Health literacy is related to age and socio-economic status. Therefore, income has also been considered a control variable (Hannemann et al., 2021).

Table 1 illustrates the constructs, scales, and items used in this study.

Table 1: Measurement Constructs and Scales

Construct and source	Scale	Items	Cronbach's Alpha
Intention to adopt (DV) *Adapted from Uncovska et al. (2023) & Zhang et al. (2019)*	7-point scale	Q1. a) I am generally willing to use mobile health apps. b) I predict I would use mobile health apps in the future. c) I plan to use mobile health apps in the future.	0.925
Trust in technology (IV) *Adapted from Mckneight et al. (2011), Shareef et al. (2014) & Pavlou (2003*	7-point scale	Q2. a) I trust mobile health apps to function as expected with the features necessary to complete the task. b) I trust mobile health apps to fulfill the expected responsibilities. c) I believe mobile health apps are consistent, predictable, and reliable. d) I trust mobile health apps to ensure data integrity and completeness during transmission, processing, and storage. e) I trust mobile health apps to ensure data accuracy when collecting my personal health data. f) I believe mobile health apps are safe to use. g) Overall, I believe mobile health apps are trustworthy.	0.920
Perceived risk (Mediator) *Adapted from Zhang et al. (2019), Akbar et al. (2020), Shareef et al. (2014) & Hong et al. (2013)*	7-point scale	Q3. a) I am concerned about the information safety of mobile health apps. b) I am concerned about the clinical safety of mobile health apps. c) I am concerned that mobile health apps may fail or malfunction. d) I am concerned about the quality of information presented incl. incomplete or incorrect information. e) I am concerned that mobile health apps fail to respond to health dangers or give faulty alarms. f) I am concerned that my personal health information which is stored in mobile health apps is not protected from unauthorized access or may be leaked. g) I believe it would be risky to store my personal health information in mobile health apps.	0.861

3.2 Data Collection

Data were collected through the administration of an online survey of individuals living in Germany and who are above the age of 18. A survey method is useful for examining the relationship between the key variables and aids in answering the proposed hypotheses. The survey is cross-sectional. Data was collected at one point in time (26.- 28. April 2023).

A survey design presents a quantitative description of the behavior of individuals in Germany regarding the intention to adopt mobile health apps by studying a small sample of that population. Internet-based surveys offer unique capabilities. They are cheap to conduct, and the web enables nearly instantaneous transmission of surveys to potential participants. Hence, the delivery and response times are faster than older survey methods. They are convenient and easy for the recipient, increasing the response rate (Fricker & Schonlau, 2002). Also, questionnaires have the advantage of reaching a wider audience than interviews. However, one disadvantage is that it is impossible to customize the questions, as can be done with other data collection methods (Hemachandra, n.d.).

The Qualtrics XM platform, which is a web-based survey tool to perform survey research, was used as the survey instrument. The survey was distributed using Prolific, an online platform that helps recruit study participants. The benefits of such a platform are a more diverse and representative sample. Asking friends and family to participate in this study would have led to a more homogenous sample in terms of a similar social and economic environment. In addition, friends and family are likely to share similar characteristics (e.g., interest in healthcare innovation), which can lead to a less diverse sample. Online platforms allow for greater diversity and can enhance the generalizability of the findings. Also, using such online platforms is time-efficient.

The survey took approximately 4 minutes to complete and was created in German language. Even though some people living in Germany may not speak German, it was assumed that more people living in Germany do not speak English well enough to understand the true meaning of the survey questions. Hence, to avoid loss of meaning through translation, the survey was created in the German language. The survey was piloted on five individuals who provided feedback on instruction and question clarity.

3.4 Data Preparation

Data were analyzed after the appropriate data quality steps were taken. Before starting the data analyses, the raw data needed to be cleaned. The initial dataset consisted of 207 participants. However, 4 participants did not fit the inclusion criteria and had to be removed from the dataset. The ‘Force Answer’ setting in Qualtrics XM ensured no responses had missing values for the primary constructs. Toward the end of the survey, participants were asked to select ‘Strongly Disagree’ for this question if they were still paying attention to the survey. 1.03% of participants failed the attention check. Therefore, another two participants had to be excluded from the survey. The beginning of the survey included three enthusiasm questions. The responses with missing values for these questions were not deleted since it does not affect the analyses of the primary constructs. Next, the dataset was checked for outliers using the Mahalanobis distance measure. Four outliers were detected and had to be removed from the dataset. Consequently, the final sample consisted of 197 participants.

3.5 Data Analysis

The statistical software used to find answers to the research questions is IBM SPSS Version 28. Before the start of the data analysis, the dataset was cleaned and prepared, including removing participants who do not fit the inclusion criteria. The mediation analysis follows the procedure described by Hayes (2018). Additional data analyses were conducted to answer the sub-research questions of the present study.

CHAPTER 4: RESULTS

The following chapter presents the results of the statistical analyses of the mediation model (H1-H4) after presenting the descriptive statistics. The analyses explore the relationship between trust in technology and intention to adopt and the mediating effect of perceived risk. Furthermore, this chapter presents the results of additional analyses that have been conducted to investigate the sub-research questions of this study.

4.1 Descriptive Statistics

After three days, 207 people completed the survey. Inclusion criteria required participants to be at least 18 years old and living in Germany and to fill out the survey in its entirety. After removing invalid responses, the final sample includes 197 participants. Confidentiality was warranted as participation was anonymous and voluntary. All participants gave consent to use their data for this study.

Table 2 summarizes the descriptive statistics of the sample profile. The average age of participants is 30.17, with the youngest being 18 years old and the oldest 83 (Figure 2). 66.5% of participants were male, and 32.5% were female (Figure 3). 24.4% indicated that their highest level of education was a master's degree or higher, 32% a bachelor's degree, 29.4% a high school diploma, 12.2% finished middle school, and 2.0% finished primary education (Figure 4). Further, 13.2% indicated that their yearly household income is below 10.000€, 47.2% an income of 10.000€-50.000€, and 19.3% an income of 50.000€-100.000€. 8.1% indicated that their annual household income is over 100.000€, and 12.2% did not specify (Figure 5).

Table 2: Descriptive Statistics of Sample Profile

Age		**Gender**		**Education**		**Income**	
	Statistics		*Frequency*		*Frequency*		*Frequency*
Mean	*30.17*	Male	*131*	Primary Education	*4*	<10.000	*26*
Minimum	*18*	Female	*64*	Middle School	*24*	10.000-50.000	*93*
Maximum	*83*	Non-binary	*1*	High School	58	50.000-100.000	*38*
		Not specified	*1*	Bachelor	*63*	+100.000	*16*
		Total	*197*	Master or higher	48	Not specified	*24*
				Total	*197*	Total	*197*

The graphs below illustrate the sample profile of study participants.

Figure 2: Graph of Age Frequencies

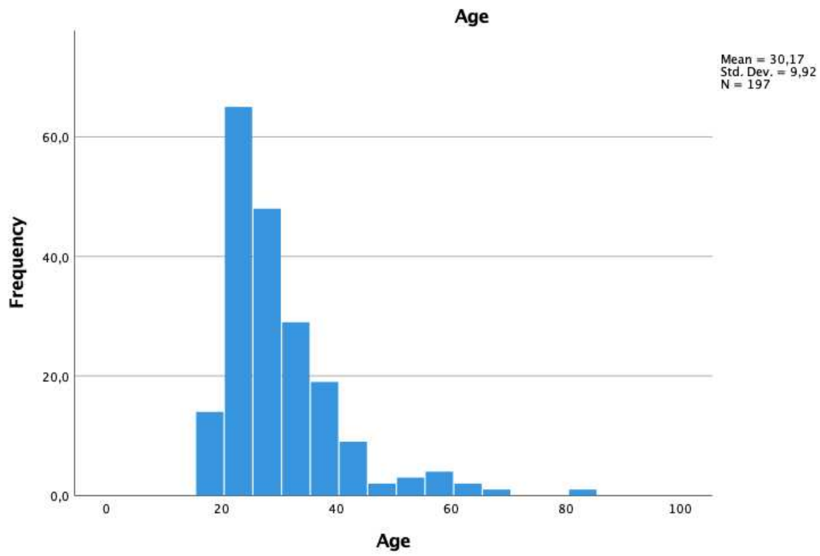


Figure 3: Graph of Gender Distribution

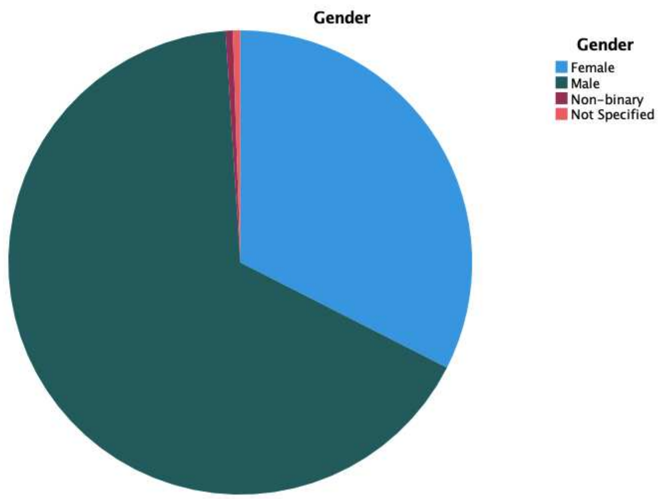


Figure 4: Graph of Education Level Distribution

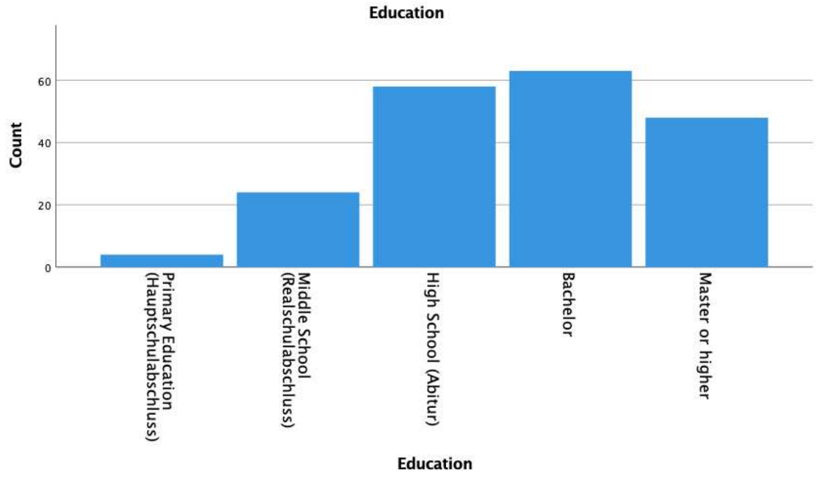


Figure 5: Graph of Yearly Household Income Distribution

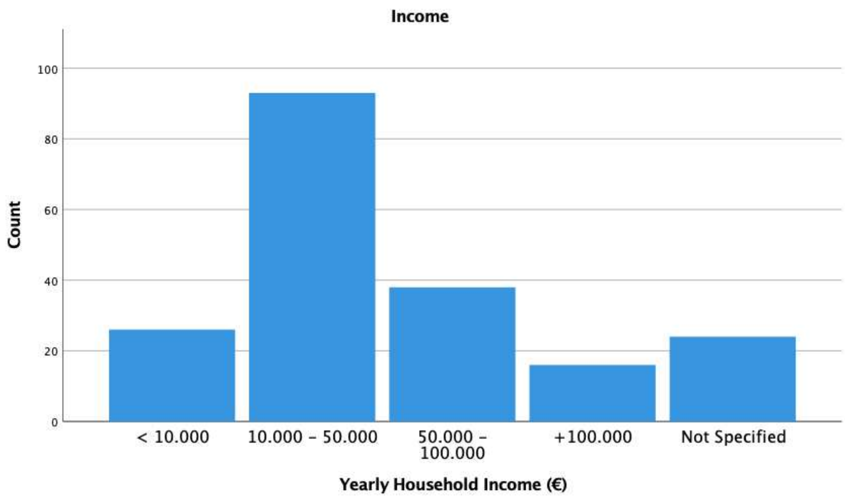


Table 3 displays the descriptive statistics of the main variables of interest following data preparation. First, there were no missing values for any of the variables of interest. Next, these statistics offer insights into the dataset's characteristics before the data analyses. For example, the mean intention to adopt of 5.2386 shows that respondents in this study have a moderate intention to adopt. The mean trust in technology of 4.9558 indicates that the distribution of participants who trust in technology and those who do not is almost even. Last, the mean perceived risk of 3.9710 indicates that participants perceive a moderately low level of perceived risk.

Table 3: Descriptive Statistics of Main Variables

	Intention to adopt	*Trust in technology*	*Perceived risk*
N=	197	197	197
Missing	0	0	0
Mean	5.2386	4.9558	3.9710
Median	5.6667	5.1429	4.0000
Mode	7.00	5.00	3.86
Std. Deviation	1.44829	1.05266	1.13159
Minimum	1.00	1.00	1.14
Maximum	7.00	7.00	7.00

4.2 Reliability Analysis

A reliability analysis for each primary variable has been conducted. This is important to ensure that the measurement scales used in this study are reliable before proceeding with the data analyses. The results of the reliability analyses can be viewed in Appendix 4. The Cronbach alpha for the dependent variable 'intention to adopt' is 0.925, the Cronbach alpha for the independent variable 'trust in technology' is 0.92, and the Cronbach alpha for the mediating variable 'perceived risk' is 0.861. A Cronbach alpha of 0.8-0.9 is adequate. 0.9 or higher is considered excellent and indicates high reliability and internal consistency (Zeller, 2005).

4.3 Correlation Analysis

Since the main variables of interest have been computed into scale variables, they are now considered metric variables. Therefore, a Pearson Correlation analysis will be performed to see if there is any significant relationship between the variables. The correlation matrix (Appendix 5) shows that all variables correlate significantly.

4.4 Inference Statistics

As this study investigates a mediating relationship, the mediation model will be analyzed using PROCESS in SPSS. Mediation models are modified forms of linear regression; therefore, the assumptions are the same (Preacher & Hayes, 2008). Linearity, normality, independence, homoscedasticity, and multicollinearity are critical assumptions to make valid inferences from regression.

A scatterplot has been created to check for linearity between the dependent and independent variables. The residuals on the scatterplot show a moderate positive linear relationship. Hence, linearity can be assumed. The Kolmogorov-Smirnov test has been performed to test for normality. The p-value is smaller than 0.001. Therefore, the distribution is not normally distributed. The histogram confirms that the dependent variable has a negatively skewed distribution. In addition, a scatterplot indicates that the model cannot prove homoscedasticity. Therefore, the dependent variable was transformed using Log10, attempting to achieve normality. However, the log transformation improved the skewness level only slightly (from -0.967 to -0.130). The decision was made to retain the original variable in its untransformed form. See Appendix 7 for all assumption tests.

Several questionnaire items captured the variables of interest. In linear regression, the normal distribution of the individual variables is less crucial. It is more important that the models are normally distributed after running a full model regression analysis. Hence, a simple linear regression has been performed to check the assumptions further (Appendix 8). The results indicate that the assumptions of normality, linearity, and homoscedasticity were met. The distribution of the residuals appears to follow a relatively normal pattern. In addition, the relationship between the independent variable and the dependent variable illustrates a linear trend. The variability of the residuals suggests the presence of homoscedasticity. Last, a collinearity test has been done to check for multicollinearity. The VIF scores are below the threshold of 5 (Marcoulides & Raykov, 2019). Hence, multicollinearity is not an issue in the present study. Often, a small sample size may not allow to hold the assumptions fully. However, regression models are generally very robust. In particular, when using Likert scales to capture the variables, the models are usually reliable.

4.5 Regression Analyses

The following presents the results of the statistical analysis of the mediation model (H1-H4), including the control variables using PROCESS. An overview of the results can be viewed in Appendix 9.

Before starting the mediation analysis, a Pearson correlation including all four control variables has been conducted to identify which control variables are significantly correlated with any of the main variables of interest. Results show (Appendix 6) that gender is significantly correlated with the independent and dependent variables, while education is significantly correlated with the dependent and the mediating variable. Therefore, gender and education will be included in the regression analyses, while age and income will be excluded.

Hypothesis 1 proposed that there is a positive relationship between trust in technology and intention to adopt. Results indicate that the direct effect, measured in the presence of the mediator, is statistically significant ($B= 0.7337$, $t= 7.6379$, $p= 0.000 <0.05$), and the relationship between the variables is positive. Hence, H1 is accepted.

Hypothesis 2 proposed a negative relationship between trust in technology and perceived risk. Results show that a negative relationship does exist ($B= -0.5842$, $t= -8.9969$, $p= 0.000$). The relationship is statistically significant to a 1% significance level. Therewith, H2 is accepted, and it can be concluded that the higher (lower) the level of trust in technology, the lower (higher) the perceived risk.

Hypothesis 3 proposed a negative relationship between perceived risk and intention to adopt and suggested that the lower the level of perceived risk, the higher the intention to adopt. Results stress that the relationship is indeed negative; however, not statistically significant ($B= -0.0496$, $t= -0.5545$, $p= 0.5799$). Hence, this study fails to reject the null hypothesis.

Hypothesis 4 considers the indirect effect of trust in technology on the intention to adopt through perceived risk. However, looking at the bootstrap intervals of the indirect effect, results show that there is a zero between the lower and upper confidence intervals (BootLLCI= -0.0754, BootULCI= 0.1358). This indicates that there is no mediation present.

4.6 Additional Analyses

To answer the sub-research questions, this study employed a descriptive statistical analysis with particular emphasis on the means of the individual survey items of the construct's trust in technology and perceived risk. The aim was to compare the average scores obtained from participants. This allows us to draw conclusions on how participants rate the trust and risk factors identified through previous literature. An overview of the means of the individual survey items can be viewed in Appendix 2.

Last, the enthusiasm check questions have been analyzed to understand how enthusiastic study participants are about mobile health apps. This may allow us to draw further conclusions on the regression results. Results show that 70.1% of respondents own at least one health app. Of these respondents, 56.9% still use the health app, and 24.4% indicated owning more than one health app. These numbers show that the sample may be biased because most respondents may already have a favorable stand on the intention to use.

CHAPTER 5: DISCUSSION

The aim of this chapter is to discuss the findings by building a deeper understanding and trying to address the research questions. This will contribute to a holistic appreciation of the proposed model. The chapter provides insights into the sub-research questions and then analyzes the hypotheses to answer how trust in technology could be explained to influence the intention to adopt and how perceived risk mediates this relationship.

Findings show that trust in technology seems to be positively correlated with the intention to adopt and is negatively correlated with perceived risk. There is no significant evidence that perceived risk has a negative effect on the intention to adopt. Second, the results stress that perceived risk does not seem to act as a mediator on the relationship between trust in technology and intention to adopt. The highest-rated determinants of trust appear to be functionality, expectations to fulfill the app's responsibilities, e.g., getting the job done, consistency, predictability, and reliability, and the highest-rated determinants of perceived risk are related to personal health information and data security.

5.1 Descriptive Statistics

The mean age of study participants is 30.17 years. In 2021, the average age of the German population was 44.7 and has been steadily increasing since 2011 (Davies, 2022). Hence, the sample consists of a younger demographic compared to the actual population, which influences the generalizability of this study. Younger people have higher technical readiness but fewer health risks. Thus, it is reasonable to infer that younger people are more inclined to adopt new technology, including mobile health apps. Encouraging older adults to adopt these apps is becoming increasingly important due to the trend of population aging within the German population. The difference between the sample average age and that of the total population may introduce a limitation in terms of accurately capturing the adoption behavior of individuals. However, although the sample consists of a younger demographic, it does not deviate significantly from the overall population and may still be considered relatively representative, allowing for a certain level of generalizability.

70.1% of study participants own at least one health app, whereas a study by Messner et al. (2020) found that only approximately 29% of Germans are using at least one health app. This may indicate that participants are more enthusiastic than the actual population leading to a sample bias towards individuals who are more interested and familiar with health-related technology. This discrepancy influences the external validity of the study. Therefore, future research may collect a larger sample with a greater age range.

Although this study did not find a significant effect of age on the variables of interest, it is relevant to consider findings from previous research. Rasche et al. (2018) investigated health app use among older adults in Germany and found that factors related to age, such as technical readiness, computer literacy, and health status, influence health app use. Also, a German cross-sectional study on the use of digital health technologies during the COVID-19 pandemic found that the use of digital health technologies correlates with the degree of health literacy and that health literacy is influenced by socio-demographic characteristics such as age. In addition, the present study included a larger proportion of male participants (66.5%) while the gender distribution of the current population of Germany is 49.23% male and 50.77% female (Statistisches Bundesamt, 2016). This introduces bias in the sample composition and creates concerns about the external validity.

The sample descriptive statistics highlight the limitations associated with the sample collected. First, the relatively small sample size may impact the robustness of the results. A larger sample would have offered greater statistical significance. In addition, the gender distribution of the study sample differs from that of the general German population. This imbalance may create bias and limit the generalizability of the results. In addition, since different age groups have different health concerns and are potential health app users, the lack of representation of different age groups is a notable limitation.

In conclusion, the sample descriptive statistics discussed in this chapter offer insights into the impact of the methodology on the study's findings. The small sample size, the unbalanced gender distribution, and the limited representation of age and socio-economic diversity require critical consideration when interpreting the results and their broader implications.

5.2 Discussion of Hypotheses and Research Questions

Sub-RQ1: What factors influence trust in mobile health apps?

Previous literature identified a number of factors influencing online trust. Some of these factors have been adapted to measure trust in mobile health apps. According to Mcknight et al. (2011), trusting beliefs increase when individuals find that the technology in question contains attributes such as functionality, reliability, and helpfulness. This stance was reinforced as study results show that participants rated survey items related to functionality the highest among all trust items. The attribute to fulfill the expected responsibilities was rated second-highest. Other attributes mentioned by McKnight et al. (2011) are consistency, predictability, and reliability. These have been rated third-highest among the trust items. Items related to data accuracy of personal health information and data integrity and completeness are rated lowest. These findings suggest that individuals place more trust in the attributes of the technology itself and have confidence in the performance of the technology, while the human influence (data accuracy and integrity) seems to cause greater concern and fear in individuals. Hence, individuals may place trust in the technological aspects but perceive larger risks in relation to human elements, which may lead to lower trust. The concerns arise from various factors discussed in Chapter 2, such as the potential for unauthorized access and breaches, the misuse of sensitive data, and the vulnerability of personal health information (Shareef et al., 2014).

This aligns with the findings from Vayena et al. (2018), who presented 73 studies that found data safety and privacy crucial to trust. Findings also align with Rauer (2012), who states that German citizens have extreme views on privacy protection. These deep-rooted privacy views may explain the low adoption in Germany. However, Germany is already known to be a "hard-line privacy country" (Rauer, 2012, p. 3) with strict data protection laws. Therefore, one would assume that German citizens would be more trusting since the state makes great efforts to ensure the data protection of its citizens.

To summarize, human-related factors may be the biggest impediment to trust in technology rather than the performance of the technology itself. However, these findings need to be explored more thoroughly by future research.

Sub-RQ2: What are the perceived risks associated with mobile health apps?

The means of individual survey items measuring perceived risk show that individuals are most concerned about personal health information being unprotected from unauthorized access or that data may be hacked. This is consistent with findings by Hsieh (2015), who found that, in the context of healthcare, perceived risk involves privacy risks such as data leakages and the potential loss of confidential data. Individuals' subjective beliefs play a role in perceived risk. Even though a certain level of risk must be accepted when sharing personal health information, many individuals misunderstand or are unaware of what personal health information is collected and how the data is used (Hasan et al., 2021).

The findings also align with a study by Fox & Connolly (2018), who found that risk beliefs are mostly related to high privacy concerns, particularly in disclosing health data. Further, past research states that mHealth users perceive risk when protecting their personal health information is not verified (Schnall et al., 2017). Users risk suffering a loss while using health app technology (Schnall et al., 2017). Hence, if a mHealth app user "perceives the risk of disclosure of their personal health information to be low, then they are more likely to use a mHealth app" (Schnall et al., 2017, p. 3).

Participants were less concerned that the technology fails to respond to health dangers or gives faulty alarms. This aligns with the findings of the trust items, which showed that individuals place more trust in the functionality of the technology itself.

RQ1: How does trust in technology influence the intention to adopt mobile health apps among individuals in Germany, and does perceived risk mediate this effect*?*

Findings confirm that trust in technology is positively related to the intention to adopt. This finding is consistent with findings from (Pavlou, 2003; Rauer, 2012; Schnall et al., 2017), who suggest that higher levels of trust enhance the willingness to adopt, and that trust is a crucial component of successful adoption of services involving uncertainty.

Besides being an essential determinant of the adoption of mobile health apps and a crucial construct for understanding individuals' perceptions of technology, trust is also considered a risk reducer (Hsieh, 2015; Weck & Afanassieva, 2023). The results of this study indicate that individuals who have a high level of trust in technology perceive less risk. This finding is consistent with previous literature, which proposed that trust is likely to develop if the perceived risk and uncertainty with the use of medical technologies can be minimized (Vayena et al., 2018) and that a lower level of perceived risk leads to a higher level of trust (Mou et al., 2017; Schnall et al., 2017). In addition, past research found institutional trust to have a negative effect on perceived risk (Hsieh, 2015). Another study found that the perception of higher risk lowers trust and that trust increases behavioral intentions by reducing perceived risk (Bansal et al., 2010).

Literature suggests that perceived risk is a significant barrier to technology adoption (Hasan et al., 2021). Given the uncertain context of health app technology, it was hypothesized that perceived risk would lower the intention to adopt mobile health apps since reducing perceived risk is expected to influence the willingness to transact (Pavlou, 2003). Past research on online marketplaces found that customers would be willing to transact if their perceived risk was low. The reason is that perceived risk enhances the anticipation of a negative outcome and, in addition to that, leads to a dismissive attitude that usually results in a negative influence on a user's intention to use (Hsieh, 2015). Results of the present study cannot confirm the findings of the existing literature. Nevertheless, logic suggests that the open nature of mobile and information technology creates uncertainty. Risk is crucial to digital health technologies (Pavlou, 2003).

There are two potential reasons why this study could not find a significant relationship between perceived risk and intention to adopt. First, although examples of different mobile health apps were presented at the start of the survey, the present study did not differentiate between those used for fitness purposes and those intended to manage specific illnesses. Hence, it could be possible that participants associated mobile health apps mainly with tracking fitness and therefore perceive less risk. Individuals often perceive high risk when tracking more sensitive health issues (Fox & Connolly, 2018). In a study by Fox & Connolly (2018), several participants perceived low levels of risk in relation to digital health technologies. Participants of this past study suggested that using mHealth technologies to track fitness is harmless and can help with healthy aging. Second, the enthusiasm check questions in the present survey showed over 50% of participants already use at least one health app. It can be assumed that individuals already using mobile health apps are less likely to be concerned about the potential risk involved. In contrast, individuals who perceive a high level of risk are likely to resist adopting them.

The results of this study showed no evidence of a mediation effect. This finding is inconsistent with existing research by Mou et al. (2017), which indicated that, although no full mediation effect was found, risk partially mediates the effect of trust on acceptance. The authors further supported the causal logic that sees trust as a precondition for risk perception. However, other factors might influence the relationship between trust and online behavior in addition to perceived risk. Pavlou (2003) found that trust acts indirectly on the intention to transact through perceived risk and that perceived risk was strongly related to intentions to transact. However, it was also found that, on average, trust has a stronger relationship with intention than risk perception does. Hence, trust might be the more relevant of the two in giving explanations of online behavior (Mou et al., 2017).

To conclude, this study investigated whether perceived risk acts as a mediator in the relationship between trust in technology and intention to adopt. The mediation analysis shows that perceived risk did not act as a mediator in this relationship.

5.3 Appreciation of the Model Trust, Risk, and Intention to Adoption mHealth

Several past studies investigated the acceptance, adoption, implementation, and use of digital health technologies on the basis of the Technology Acceptance Model (TAM) or an extension of it. Notable is the application of TAM in the prediction and explanation of end-user reactions to health IT. TAM was developed in the 1980s (Holden & Karsh, 2010) and focuses on the factors determining an individual's adoption of a given technology. It includes two key factors determining the behavioral intentions of individuals to adopt and use a specific technology: "Perceived Usefulness" (PU) and "Perceived Ease of Use" (PEOU) (Cho et al., 2014). Several modifications of TAM exist. Almost every study added variables to gain a better understanding of the determinants of health IT use behavior (Holden & Karsh, 2010). For example, Ortega Egea & Román González (2011) proposed an extension of TAM with trust and risk factors to explain physicians' acceptance of EHCR systems. However, the amount and variety in model specification limit the comparison across studies. Scholars criticized research for arbitrarily adding variables leading to an increasingly less coherent theory. Since TAM was initially developed outside of health care, some of its main constructs and measures might not be relevant to healthcare examinations (Holden & Karsh, 2010).

It is important to discuss some advantages and disadvantages of proposing a new model compared to building upon an established model, like TAM. The most obvious advantage is novelty. By proposing a new model, the present study contributes to the field by providing a new perspective on the relationship between the variables. The simplicity of the mediation model also allows a clear and focused understanding of the relationship between the constructs. In addition, a tailored model may be more fitting for the research objectives and can allow examining previously unexplored factors of trust in technology. By tailoring the model to fit the research objectives of this study, greater control was ensured over the measurement instruments used.

On the other hand, building upon established models might offer a strong theoretical grounding and may increase the credibility of the findings. Also, oversimplification is a potential risk when creating a simple mediation model of complex variables like trust. In many cases, using or extending an established model might increase comparability across studies. However, as explained by Holden & Karsh (2010), continuously creating new versions and extensions of TAM leads to confusion and a less coherent theory. Therefore, in light of the research objectives of this study, it is valuable to propose a new model attempting to explain the relationship between the variables of interest to expand the theoretical landscape and make an original contribution to the subject field.

Furthermore, it needs to be critically evaluated if the choice of measurement instrument was most suitable for the present research questions. The survey method was used to collect numerical data on the variables of interest, allowing us to analyze the strength and direction of the relationships between the variables. This quantitative approach examined trust in technology, perceived risk, and intention to adopt using adapted measurement scales from previous research. The survey contained seven items each for the independent and mediating variable, allowing to satisfactorily capture respondents' feelings and opinions. In addition, the use of quantitative measures allowed for statistical analyses, which helped to explore the relationships between the variables.

5.4 Theoretical Implications

This study contributes to ongoing research in different ways. Past research has set out to explore how trust in digital health technologies can be increased (Korn et al., 2022) and to clarify the role of trust in the health context (Fox & Connolly, 2018). Hsieh (2015) encouraged future research to explain the role of trust and risk perception. This study contributes to the existing body of research on trust and perceived risk in digital health technologies and adoption behavior by highlighting the significance of trust on (health app users') adoption intention.

Particularly, this study has shown that the uncertainty associated with new/unknown technology raises concerns about potential risks, such as the misuse of personal health data and privacy breaches. These perceived risks cause individuals to be fearful and reluctant. It seems logical for individuals to be reluctant to adopt new/unknown technology as it puts them in a vulnerable position, not only with the technology but also with institutions and people involved in developing it. This study sheds new light on the difference between trust factors that are specific to technology versus human-related factors and underlines the importance to create confidence in technology's functionality, reliability, and security. Confidence in the attributes of technology help overcome individuals' concerns and makes them more inclined to adopt the technology.

Little research exists on trust in technology (Mcknight et al., 2011). In addition, there was a need to explore the determinants of trust in digital health, such as presented by previous authors (Adjekum et al., 2018) Trust in technology had not yet been studied in this context. The factors affecting trust in technology differ from those affecting trust in humans. Hence it is appropriate to focus on trust in technology and to consider the concept independently to get a deeper understanding of the determinants of trust in mobile health apps. Findings show that people have greater trust in technology attributes such as functionality, reliability, consistency, and predictability than human-related factors such as ensuring data accuracy when collecting personal health information and data integrity and completeness.

A possible explanation is that technologies are not moral agents, whereas humans are. The involvement of humans introduces negative motives. For example, malicious intent can lead to data breaches and other privacy violations. Institutions may misuse health data for personal gain, which could lead to the stealing or leaking of confidential data. App developers may neglect necessary security measures. Risks caused by humans might be more serious and may cause greater harm to individuals than technology-specific risks. This could explain why people have lower trust in human-related factors compared to trust in technology attributes, which makes them critical to technology adoption.

Further, this study adds to the discordant literature on the association and direction of causality between trust and risk (Mou et al., 2017) by identifying that trust in technology is negatively related to perceived risk. The study provides insights into the dynamics between trust in technology and perceived risk in the context of health app adoption. Perhaps trust is built independently of perceived risk. When it comes to adopting technology, perceived risk may play a role in the willingness and decision to use it. With this in mind, distrust towards mobile health apps may be enough to deter individuals from adopting them. Potential users weigh the risks involved against the expected benefits and functionality of the technology. If the perceived risk is high, individuals may resist or hesitate to use the technology. Distrust can arise for various reasons like concerns about privacy, data security, and fear about the accuracy and reliability of the technology.

Past research investigated perceived risk as a mediating variable in the relationship between trust and intention to transact. Scholars found the perceived risk to have a significant mediating effect. However, the present study could not find a significant mediation effect. A possible explanation could be that additional factors, such as perceived usefulness and perceived ease of use, as the TAM Model shows (Cho et al., 2014), influence the present model. Perhaps perceived risk is not the only mediator which explains the relationship between trust in technology and intention to adopt. It is possible that multiple mediators explain the relationship. As mentioned, trust and perceived risk could be independently related to adoption intention.

5.5 Limitations and Future Work

A qualitative interview method might have provided deeper insights into individuals' thought- and decision-making processes and could have identified additional determinants of trust in technology and perceived risk. Qualitative methods have the potential to capture more nuanced data that allow for a deeper investigation of an individual's feelings and opinions. Nevertheless, qualitative methods also have limitations regarding generalizability and the ability to measure the relationships between the variables quantitively (Queirós et al., 2017). Future work may consider a mixed-methods approach to achieve a more comprehensive understanding of the sub-research questions presented in this study. Using a mixed-methods design, researchers can collect numerical data for statistical analysis while gaining in-depth qualitative insights (Creswell, 2014). This would enable a more holistic investigation.

Second, the measurement scales used in this study have been appropriate to examine the *main research question* and gave us a valuable overall understanding of the factors of trust and perceived risk and the relationship of these variables on adoption intention. However, the measurement scales may not have been most appropriate to investigate the *sub-research questions* presented in this paper or subtleties on the relative importance of some presented options. While Likert scales are among the most commonly used measurement scales (Munshi, 2014) and were used to some extent to measure the main variables of this study, alternative measurement tools may provide additional insights and can provide different results. For example, a prioritization scale could have provided a richer understanding of the trust and risk factors that are most important to individuals. This might have increased the capacity to extrapolate results and enhanced the validity and reliability of the study's constructs. Hence, future work may use alternative measurement scales to get a deeper understanding of these complex constructs.

Third, although this study identified several trust and risk enablers/impediments, certain dimensions were not included in the survey. For example, one of the trust attributes identified by Mcknight et al. (2011) was not included in the survey questions. The omission limits the scope of the trust in technology study. In addition, Pavlou (2003) identified several types of risks. However, the survey questions in the study focused mainly on performance and privacy risks and neglected economic and personal risks. Hence, the survey instrument has not captured the full range of risk perceptions relevant to mobile health app adoption. For this reason, the results are limited in providing a comprehensive picture of the various trust and risk factors. Future work could include a full range of trust and risk factors to create a more holistic understanding of the factors influencing the intention to adopt. Including a broader range of factors that promote/inhibit trust and providing a more comprehensive assessment of various risk dimensions will improve the validity and generalizability of the findings.

Fourth, the sample size was relatively small, which can potentially affect statistical assumptions. A larger sample can strengthen the robustness and external validity of the findings. In addition, the gender distribution of the study does not fully represent the general German population. Also, the sample does not accurately represent the population in terms of age and socio-economic status. Diverse age groups are particularly important in this context, as older people are likely to have more serious health concerns and are important potential health app users, especially in light of the aging society. Future work should collect a larger sample that more accurately represents the German population in terms of gender and age distribution and socio-economic background. In addition, cluster analyses could be performed to investigate the older age groups in more detail. Increasing the sample size and collecting a more diverse sample in terms of demographics can give more robust results.

Fifth, previous research indicated several variables influencing the relationships under study. Health literacy and technical readiness are two of many factors found to influence adoption behavior. These variables could have potentially impacted the results and may be included in further investigations. A larger range of variables provides a more comprehensive understanding of health app adoption behavior. Future work should consider integrating additional factors into the model to investigate the effect of these variables further and increase the explanatory power of the model.

5.6 Recommendations for mHealth Providers, Regulators, and Policymakers

mHealth Providers

The introduction of DiGA has brought several benefits. Concrete measures have been implemented which may increase trust in mobile health apps. According to Dahlhausen et al. (2021), healthcare professionals' level of trust in DiGA would increase through recommendations from reliable sources, like scientific societies, medical associations, and peers. This increased level of trust may foster adoption. Health app providers should adopt this stakeholder collaboration strategy and leverage the credibility of trusted medical entities to build trust among potential users. Health app providers could, for example, ask medical entities like hospitals for endorsements. They benefit from following DiGA related rules and recommendations strictly and be seen to doing so.

Online reviews have been found to induce trust in e-commerce websites (Shaheen et al., 2019). Therefore, health app providers should use online reviews and encourage users to share their experiences. They could also consider implementing an online forum function where users can share experiences and provide recommendations being open about their improvement potential as well as transparent about the way they had fixed eventual problems found in the past.

Regulators

Since data security and privacy are primary concerns for German people, regulators should stimulate the conversation on personal health information digital use as beneficial for the primary use of health data in the health and care context as well as and contributor to research and development of new medical technologies and general improvement of the healthcare system as a result of more data-informed policies. It may be worthwhile to discuss whether health data is a public good (World Health Organization, 2021). After all, everyone wants to be treated with the latest medical technology in case of illness. There are many ways to do this. For example, fostering public dialogue and organizing forums to unite relevant stakeholders.

Regulators should also raise awareness about the benefits of mobile health apps and promote digital health literacy, for example, by supporting educational campaigns. Regulators should support introducing digital health courses into school and university curricula.

Policymakers

Policymakers may implement security measures such as user authentication when accessing or changing personal health information. This is useful to provide absolute transparency and control over personal health data, including far-reaching anonymity. It should also be openly presented what kind of personal health information is being collected and stored and the purpose for which the data is stored. Presenting this information in the app for everyone to see, especially for people with lower technical readiness, is vital. This is especially important for app solutions for more sensitive health issues and chronic diseases.

Policymakers should also consider implementing a cybersecurity certification label, which can empower consumers to assess security solutions (Matheu-García et al., 2019). It is critical to protect users' privacy and confidentiality by protecting their data from breaches and unauthorized access. Or go as far as suggested by the EU-funded project Label2Enable, which is working on establishing an easy-to-understand labeling system for mobile health apps following and developing further from an international ISO norm. This EU quality label informs patients, healthcare professionals, and regulatory authorities, among others, about trustworthy mobile health apps. The project seeks to promote trust by evaluating apps against predetermined standards that ensure data security, legal compliance, and doctor-patient confidentiality (Label2Enable, n.d.).

CHAPTER 6: CONCLUSION

The main objective of this study was to examine the factors contributing to the relatively low adoption rate of mobile health apps in Germany, despite the introduction of DiGA, which enables the insurance coverage of prescribed mobile health apps. The study focused, in particular, on investigating the relationship between trust in technology and perceived risk on adoption intention. The concept of trust is multifaceted, complex and has been widely researched. To contribute additional value to the subject field, this study focused on trust in technology, a form of trust initially introduced by Mcknight et al. (2011). This type of trust has not been studied extensively in this context and, therefore, enhances the significance and contribution of this research.

The existing literature presents contrasting perspectives regarding the relationship between trust and perceived risk, particularly its strength and direction. This study attempts to clarify the relationships and associations of the variables and investigated perceived risk as a mediating factor in this relationship.

A significant mediation effect of perceived risk was not found. However, a strong positive relationship between trust in technology and intention to adopt and a significant negative relationship between trust in technology and perceived risk were found.

In addition, the analysis of the determinants of trust in technology suggests that human-related factors are greater impediments to trust in technology than technological aspects like functionality. This study also highlights the importance of privacy and data security regarding personal health information, which is a significant concern for individuals when considering the adoption of mobile health apps. Perceived risk would likely decrease and enhance adoption if there was greater transparency on the use of personal health information, including where it is stored and who has access to it.

Simulating theoretical implications have been identified, which stimulate academic work in the direction of the determinants of trust and risk in mobile health app adoption and the dynamics between the concepts. Recommendations for policymakers and regulators were extracted, particularly with regard to the need for raising awareness about the benefits of mobile health apps, promoting health literacy, and implementing security measures.

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APPENDICES

Appendix 1: A Short Summary of Trust-related Literature

Year	Author(s)	Main Ideas
2003	Pavlou	Trust is related to the positive attitude and perceived control toward the transaction with web retailers, reducing uncertainty and thereby providing behavioral intentions to transact.
2011	Mckneight et al.	Trust in technology rather than trust in people plays an important role in shaping beliefs about IS.
2014	Shareef et al.	mHealth systems face critical security and privacy challenges which influences users' decision to adopt it. Reliability is another concern when seeking services for mHealth systems.
2018	Rasche et al.	Lack of trust is a major barrier to the acceptance and usage of mobile health apps, along with data privacy concerns and fear of misdiagnosis.
2018	Adjekum et al.	Trust is critical to the willingness of vulnerable individuals to place their trust in people, institutions, or technology, and the level of associated risk can influence that willingness. Trust is impacted by an interplay of various enabling and inhibiting factors.
2020	Heidel & Hagist	Users need to trust the apps they use. Lack of interest, high prices and a lack of data security are some of the main factors for people not to use them.
2021	Hasan et al.	Trust and perceived privacy risk are central to consumer behavior, especially in the use and adoption of information technology. These factors are important when it comes to individuals' willingness to share sensitive personal data.
2021	Dahlhausen et al.	Increasing trust in DiGA through trusted bodies may foster adoption. More transparent and standardized evidence, clearly showing the effects for patients, might promote trust in DiGA.
2023	Sawrikar & Mote	Trust in technology is important in environments where there is no conventional human interaction. Trust is characterized by the perception of technology as a practical tool that serves as a

		means to an end and involves the belief that the technology is reliable and dependable.
2023	Weck & Afanassieva	Initial trust is a critical factor in technology adoption. A significant amount of technology is unfamiliar to users. Initial trust plays a crucial role in mitigating the perceived risk and uncertainties associated with technology interaction. Positive beliefs about technology facilitate the formation of trusting beliefs in non-human objects.

Appendix 2: Means of Individual Survey Items

Items on Trust in Technology	**Mean**
I trust mobile health apps to function as expected with the features necessary to complete the task.	*5.47*
I trust mobile health apps to fulfill the expected responsibilities.	*5.40*
I believe mobile health apps are consistent, predictable, and reliable.	*4.93*
Overall, I believe mobile health apps are trustworthy.	*4.79*
I believe mobile health apps are safe to use.	*4.74*
I trust mobile health apps to ensure data accuracy when collecting my personal health data.	*4.70*
I trust mobile health apps to ensure data integrity and completeness during transmission, processing, and storage.	*4.66*
Items on Perceived Risk	**Mean**
I am concerned that my personal health information which is stored in mobile health apps is not protected from unauthorized access or may be leaked.	*4.60*
I am concerned about the information safety of mobile health apps.	*4.27*
I believe it would be risky to store my personal health information in mobile health apps.	*4.08*
I am concerned about the quality of information presented, incl. incomplete or incorrect information.	*3.97*
I am concerned that mobile health apps fail to respond to health dangers or give faulty alarms.	*3.93*
I am concerned about the clinical safety of mobile health apps.	*3.86*

I am concerned that mobile health apps may fail or malfunction.	*3.09*

Appendix 3: Survey Protocol

Introduction Text

Welcome to this survey about the use of mobile health apps in Germany. This survey is part of a master's thesis research project at Católica Lisbon School of Business & Economics, the purpose of which is to understand individuals' adoption of mobile health apps.

PLEASE READ THE FOLLOWING TEXT CAREFULLY.

Mobile health apps are software applications designed to help individuals manage their health and well-being, often through mobile devices or computers. Common mobile health apps include those that record physical activity, monitor vital signs, or provide information about health and well-being.

Examples of popular mobile health apps in Germany include:

- MyFitnessPal: Tracks diet and exercise habits.

- Ada: Personalized health assessments and recommendations.

- Flo: Period and cycle calendar

- Headspace: Guided meditations and mindfulness exercises

- Apple Health: Collects health data from your iPhone

I am happy for you to participate in this online survey if you are over 18 years old and live in Germany. This survey should take about 3-4 minutes to complete. Participation is voluntary, and responses will be treated anonymously. *Do you agree to participate in this survey?*

- Yes, I agree.
- No.

Control Questions

Q1. Do you live in Germany?

- Yes
- No

Q2. Are you older than 18 years old?

- Yes
- No

Enthusiasm Check Questions

Q3. Do you have a health app?

- Yes
- No

Q4. If yes, do you still use it?

- Yes
- No

Q5. Do you have more than one health app?

- Yes
- No

Main Construct Questions

Q6. Please rate the following statements on a scale from "Strongly disagree" to "Strongly agree."

a) I am generally willing to use mobile health apps.
b) I predict I would use mobile health apps in the future.

c) I plan to use mobile health apps in the future.

Q7. Please rate the following statements on a scale from "Strongly disagree" to "Strongly agree."

a) I trust mobile health apps to function as expected with the features necessary to complete the task.
b) I trust mobile health apps to fulfill the expected responsibilities.
c) I believe mobile health apps are consistent, predictable, and reliable.
d) I trust mobile health apps to ensure data integrity and completeness during transmission, processing, and storage.
e) I trust mobile health apps to ensure data accuracy when collecting my personal health data.
f) I believe mobile health apps are safe to use.
g) Overall, mobile health apps are trustworthy.

Q8. Please rate the following statements on a scale from "Strongly disagree" to "Strongly agree."

a) Please select "Strongly disagree" for this question to indicate that you are paying close attention to the survey.

Q9. Please rate the following statements on a scale from "Strongly disagree" to "Strongly agree."

a) I am concerned about the information safety of mobile health apps.
b) I am concerned about the clinical safety of mobile health apps.
c) I am concerned that mobile health apps may fail or malfunction.
d) I am concerned about the quality of information presented, incl. incomplete or incorrect information.
e) I am concerned that mobile health apps fail to respond to health dangers or give faulty alarms.
f) I am concerned that my personal health information stored in mobile health apps is not protected from unauthorized access or may be leaked.
g) I believe it would be risky to store my personal health information in mobile health apps.

Demographics

Q10. How old are you?

____

Q11. Which gender do you identify with?

a) Male
b) Female
c) Non-binary
d) Not specified

Q12. What is your highest level of education?

a) Primary Education (Ger. Translation "Hauptschulabschluss")
b) Middle School (Ger. Translation "Realschulabschluss")
c) High School (Ger. Translation "Abitur")
d) Bachelor (Ger. Translation "Bachelorstudium")
e) Master or higher (Ger. Translation "Masterstudium oder höher")

Q13. What is your annual household income?

a) < 10.000
b) 10.000 – 50.000
c) 50.000 – 100.000
d) +100.000
e) Not specified

Appendix 4: Reliability Analysis

Reliability Statistics

Cronbach's Alpha	N of Items
,861	7

Reliability Statistics

Cronbach's Alpha	N of Items
,925	3

Reliability Statistics

Cronbach's Alpha	N of Items
,920	7

Appendix 5: Correlation Analysis

Correlations

		DV_Adopt	IV_Trust	Mediator_Risk
DV_Adopt	Pearson Correlation	1	,558**	-,308**
	Sig. (2-tailed)		<,001	<,001
	N	197	197	197
IV_Trust	Pearson Correlation	,558**	1	-,549**
	Sig. (2-tailed)	<,001		<,001
	N	197	197	197
Mediator_Risk	Pearson Correlation	-,308**	-,549**	1
	Sig. (2-tailed)	<,001	<,001	
	N	197	197	197

**. Correlation is significant at the 0.01 level (2-tailed).

Appendix 6: Correlation Between Control Variables and Variables of Interest

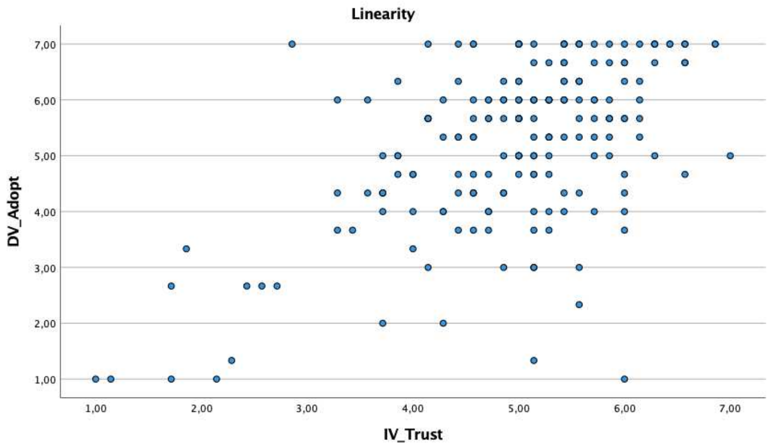
Correlations

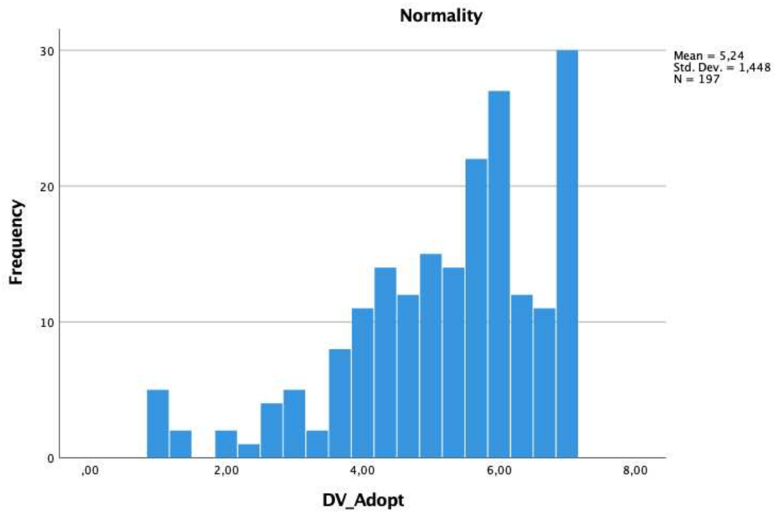
		Wie alt sind Sie?	Mit welchem Geschlecht identifizieren Sie sich?	Was ist Ihr höchster Bildungsabschluss?	Wie hoch ist Ihr jährliches Haushaltseinkommen?	IV_Trust	DV_Log	DV_Adopt	M_Risk
Wie alt sind Sie?	Pearson Correlation	1	-,042	,211**	,183*	-,042	,095	-,130	-,022
	Sig. (2-tailed)		,556	,003	,010	,560	,185	,068	,761
	N	197	197	197	197	197	197	197	197
Mit welchem Geschlecht identifizieren Sie sich?	Pearson Correlation	-,042	1	-,065	-,069	-,160*	,173*	-,177*	,082
	Sig. (2-tailed)	,556		,367	,337	,025	,015	,013	,250
	N	197	197	197	197	197	197	197	197
Was ist Ihr höchster Bildungsabschluss?	Pearson Correlation	,211**	-,065	1	,108	-,044	-,165*	,180*	,144*
	Sig. (2-tailed)	,003	,367		,130	,537	,020	,011	,044
	N	197	197	197	197	197	197	197	197
Wie hoch ist Ihr jährliches Haushaltseinkommen?	Pearson Correlation	,183*	-,069	,108	1	-,028	,025	-,008	-,038
	Sig. (2-tailed)	,010	,337	,130		,695	,724	,912	,594
	N	197	197	197	197	197	197	197	197
IV_Trust	Pearson Correlation	-,042	-,160*	-,044	-,028	1	-,505**	,558**	-,549**
	Sig. (2-tailed)	,560	,025	,537	,695		<,001	<,001	<,001
	N	197	197	197	197	197	197	197	197
DV_Log	Pearson Correlation	,095	,173*	-,165*	,025	-,505**	1	-,956**	,287**
	Sig. (2-tailed)	,185	,015	,020	,724	<,001		<,001	<,001
	N	197	197	197	197	197	197	197	197
DV_Adopt	Pearson Correlation	-,130	-,177*	,180*	-,008	,558**	-,956**	1	-,308**
	Sig. (2-tailed)	,068	,013	,011	,912	<,001	<,001		<,001
	N	197	197	197	197	197	197	197	197
M_Risk	Pearson Correlation	-,022	,082	,144*	-,038	-,549**	,287**	-,308**	1
	Sig. (2-tailed)	,761	,250	,044	,594	<,001	<,001	<,001	
	N	197	197	197	197	197	197	197	197

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Appendix 7: Assumption Tests

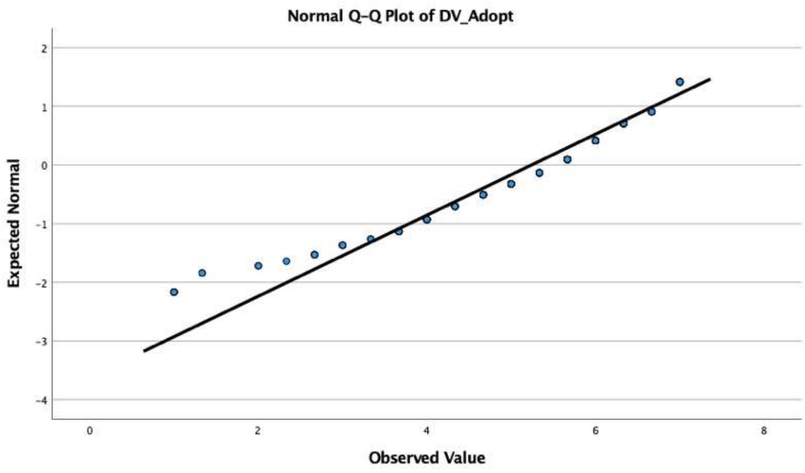


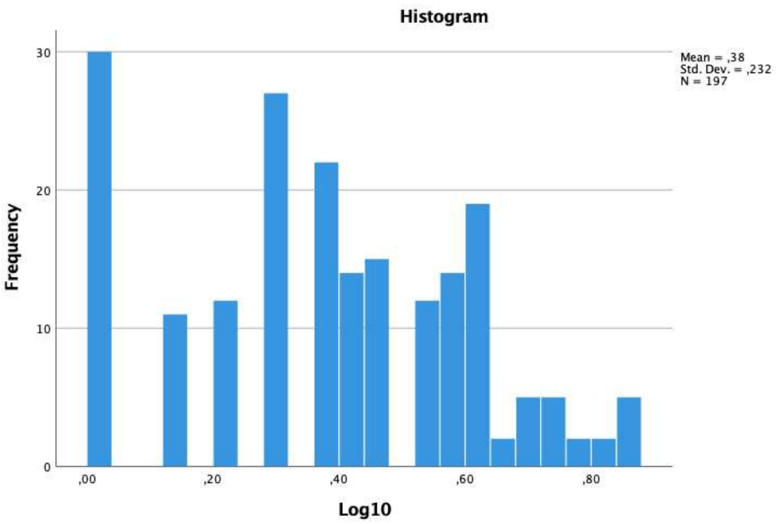


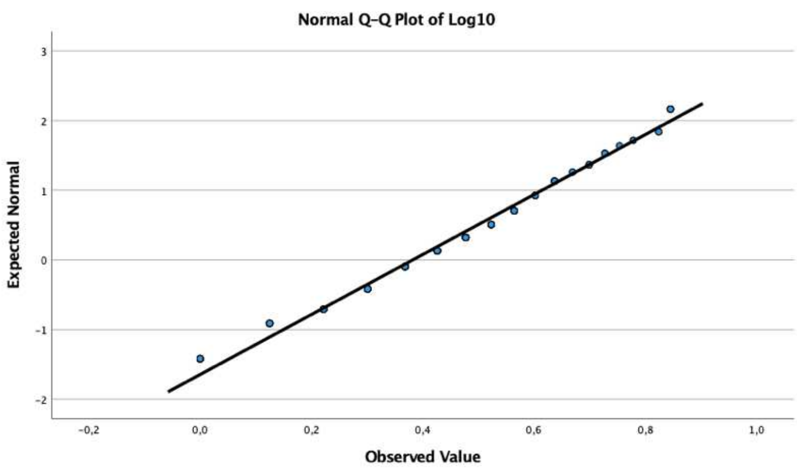
Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
DV_Adopt	,134	197	<,001	,914	197	<,001

a. Lilliefors Significance Correction


Normal Q–Q Plot of DV_Adopt
Expected Normal
Observed Value
2
1
0
−1
−2
−3
−4
0
2
4
6
8


Histogram
Mean = ,38
Std. Dev. = ,232
N = 197
Frequency
Log10
30
20
10
0
,00
,20
,40
,60
,80


Normal Q–Q Plot of Log10
Expected Normal
Observed Value
3
2
1
0
−1
−2
−0,2
0,0
0,2
0,4
0,6
0,8
1,0

Appendix 8: Linear Regression to Test Assumptions

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,558[a]	,311	,304	1,20847	1,832

a. Predictors: (Constant), M_Risk, IV_Trust

b. Dependent Variable: DV_Adopt

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	127,803	2	63,902	43,756	<,001[b]
	Residual	283,317	194	1,460		
	Total	411,120	196			

a. Dependent Variable: DV_Adopt

b. Predictors: (Constant), M_Risk, IV_Trust

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	1,465	,754		1,942	,054		
	IV_Trust	,765	,098	,556	7,793	<,001	,698	1,432
	M_Risk	-,004	,091	-,003	-,044	,965	,698	1,432

a. Dependent Variable: DV_Adopt

Collinearity Diagnostics[a]

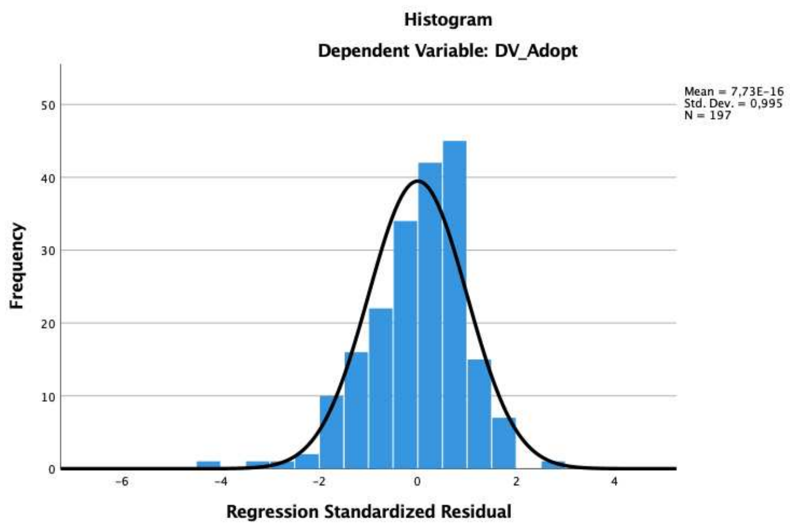
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	IV_Trust	M_Risk
1	1	2,900	1,000	,00	,00	,01
	2	,091	5,640	,00	,14	,32
	3	,008	18,494	1,00	,86	,67

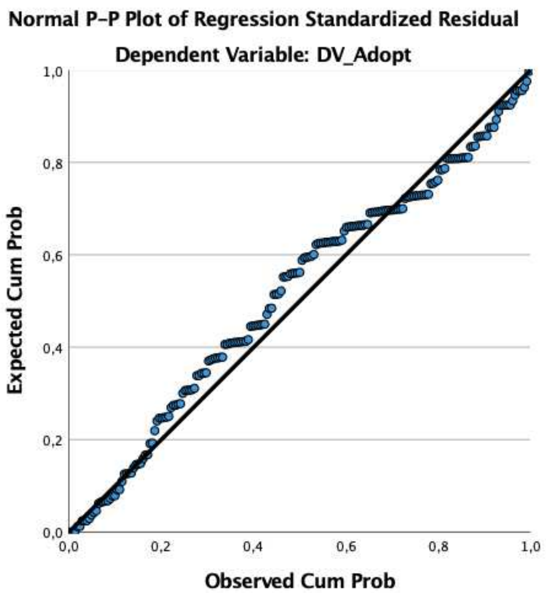
a. Dependent Variable: DV_Adopt

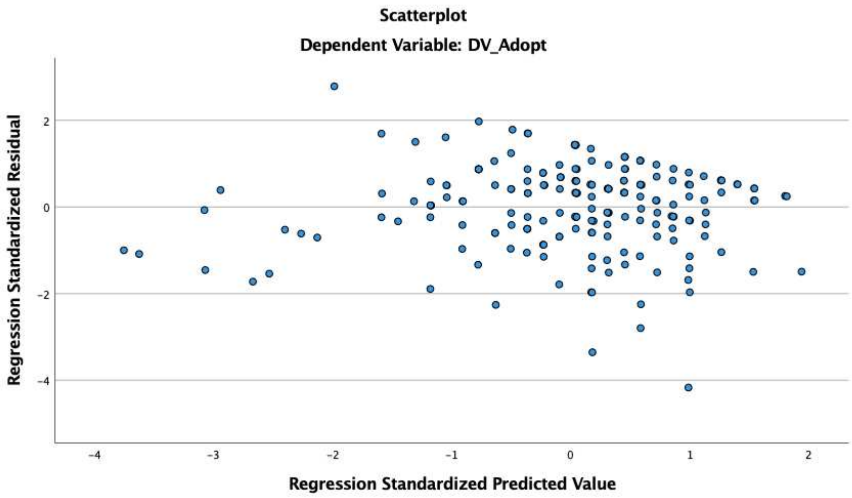
Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2,2071	6,8035	5,2386	,80750	197
Residual	-5,03590	3,36588	,00000	1,20229	197
Std. Predicted Value	-3,754	1,938	,000	1,000	197
Std. Residual	-4,167	2,785	,000	,995	197

a. Dependent Variable: DV_Adopt


Histogram
Dependent Variable: DV_Adopt
Mean = 7,73E-16
Std. Dev. = 0,995
N = 197
Frequency
Regression Standardized Residual


Normal P-P Plot of Regression Standardized Residual
Dependent Variable: DV_Adopt
Expected Cum Prob
Observed Cum Prob


Scatterplot
Dependent Variable: DV_Adopt
Regression Standardized Residual
Regression Standardized Predicted Value
2
0
-2
-4
-4
-3
-2
-1
0
1
2

Appendix 9: Regression - Mediation Analysis (Hayes PROCESS Model 4)

```
**************************************************************************
Model  : 4
    Y  : DV_Adopt
    X  : IV_Trust
    M  : M_Risk

Covariates:
 Gender   EDUC

Sample
Size:  197

**************************************************************************
OUTCOME VARIABLE:
 M_Risk

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5621      ,3160      ,8895    29,7184     3,0000   193,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     6,3802      ,5065    12,5955      ,0000     5,3811     7,3792
IV_Trust     -,5842      ,0649    -8,9969      ,0000     -,7123     -,4561
Gender        ,0069      ,1353      ,0508      ,9596     -,2600      ,2738
EDUC          ,1301      ,0648     2,0072      ,0461      ,0023      ,2580

Standardized coefficients
              coeff
IV_Trust     -,5434
Gender        ,0031
EDUC          ,1199


**************************************************************************
OUTCOME VARIABLE:
 DV_Adopt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5996      ,3595     1,3714    26,9448     4,0000   192,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1,1296      ,8490     1,3305      ,1849     -,5450     2,8041
IV_Trust      ,7337      ,0961     7,6379      ,0000      ,5442      ,9231
M_Risk       -,0496      ,0894     -,5545      ,5799     -,2258      ,1267
Gender       -,2163      ,1680    -1,2875      ,1995     -,5478      ,1151
EDUC          ,2841      ,0813     3,4931      ,0006      ,1237      ,4446

Standardized coefficients
              coeff
IV_Trust      ,5332
M_Risk       -,0387
Gender       -,0755
EDUC          ,2046
```

```
************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:
 DV_Adopt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5988      ,3585     1,3665    35,9530     3,0000   193,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,8134      ,6278     1,2956      ,1967     -,4249     2,0517
IV_Trust      ,7626      ,0805     9,4758      ,0000      ,6039      ,9214
Gender       -,2167      ,1677    -1,2919      ,1979     -,5475      ,1141
EDUC          ,2777      ,0804     3,4555      ,0007      ,1192      ,4362

Standardized coefficients
              coeff
IV_Trust      ,5543
Gender       -,0757
EDUC          ,1999

****************** CORRELATIONS BETWEEN MODEL RESIDUALS ******************

            M_Risk   DV_Adopt
M_Risk      1,0000      ,0000
DV_Adopt     ,0000     1,0000



************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_cs
      ,7626      ,0805     9,4758      ,0000      ,6039      ,9214      ,5543

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI      c'_cs
      ,7337      ,0961     7,6379      ,0000      ,5442      ,9231      ,5332

Indirect effect(s) of X on Y:
           Effect     BootSE   BootLLCI   BootULCI
M_Risk      ,0290      ,0544     -,0754      ,1358

Completely standardized indirect effect(s) of X on Y:
           Effect     BootSE   BootLLCI   BootULCI
M_Risk      ,0210      ,0395     -,0548      ,0994
```