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The Psychology of Technology – An Interdisciplinary Approach to Understand the Role of Trust in Fitness App Usage

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Vorgelegt von

Lena Maren Busch

aus Kamen (Nordrhein-Westfalen)

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Lena Maren Busch

from Kamen (North Rhine-Westphalia)

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Lena Maren Busch

University of Münster
Department of Sport Psychology
Horstmarer Landweg 62b
48149 Münster, Germany

DFG-Graduate School 1712
Trust and Communication in a Digitized World
Domplatz 6
48151 Münster, Germany

Tel.: +49 0251 8331786
E-Mail: lena.busch@uni-muenster.de

Student number: 420106

Dean:	Prof. Dr. Guido Hertel
1st examiner:	Prof. Dr. Bernd Strauß
2nd examiner:	Prof. Dr. Bernd Blöbaum
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Summary

Digitalization and the availability of technical devices such as smartphones have changed the way people work, live, and how they communicate with each other. Traditional interpersonal and analogue communication shift to communication via digital media, and also to communication *with* the media (e.g., in healthcare, sports, and exercise). Here, fitness apps have emerged as a widely used tool to track and to enhance health behavior. Fitness apps offer a range of functions (e.g., daily step count targets) and benefits. For example, fitness app usage can contribute to health behavior by enhancing physical activity and by helping to establish health related routines. Furthermore, self-tracking via fitness apps has been regarded as a means to gain objective information about one's body and to practice body awareness and body trusting. However, fitness app usage has also been associated with high dropout rates and with a range of risks. These risks can refer to technology related aspects (e.g., privacy issues, data theft) and to body related aspects (e.g., biased measurements leading to health risks). Therefore, it has created a high level of interest in the society to identify predictors, benefits and risks of fitness app usage. Beyond the background of diverse risks and benefits associated with fitness app usage, the importance of trust is raised. Trust has been defined as the willingness to make oneself vulnerable facing potential risks.

Hence, it was an overall aim of this work to understand the processes of initiation of, maintenance of, and dropout from fitness app usage beyond the background of trust research, and to gain insight into the associations between fitness app usage, trust in technology, and body trusting. To examine these questions, an interdisciplinary and heuristic research framework model was established that guided through this work. Across three studies targeting these research questions, diverse designs and methodologies were applied including cross-sectional and longitudinal, non-experimental and experimental designs (e.g., randomly

controlled trial), structural equation modelling, analyses of invariance, survival analyses, response surface analyses, and multilevel Bayesian analyses.

In a first study, critical factors associated with fitness app usage were examined, and the trust in technology model was tested in the field of fitness apps. It was found that trust in technology is a key aspect that is associated with fitness app usage. Specifically, propensity to trust can explain the initiation of fitness app usage. However, limited validity of the scales measuring institution-based trust was indicated. Trusting beliefs were found to be important in understanding maintenance of and dropout from fitness app usage, especially concerning functionality beliefs. With regards to body trusting, no substantial relations with trust in technology, fitness app usage, and exercise were found.

In a second study, a trust-based model was tested to explain fitness app usage by also considering dimensions of risk and benefit assessments. The results indicated that risk and benefit are dimensional constructs and that trust is negatively associated with risk perception. Specifically, dimensions of perceived psychological and performance benefits were associated with the intention to use a fitness app whereas perceived risks were not.

In a third RCT study using daily diary, it was tested whether six weeks' self-tracking via fitness apps and the implementation of an external step target can influence body trusting, body listening, and psychological well-being. No time, group, or time-group interaction effects were found, and trust in technology did not moderate these effects. Examining potential causality between body trusting and psychological well-being, a causal bilateral connection was found. However, after controlling for auto-correlation, the exact nature of this connection remained uncertain. Testing longitudinal effects within the model of trust in technology, propensity to trust was found to be stable over time. Nevertheless, propensity to trust did not affect institution-based trust in a causal fashion.

Overall, practice-relevant implications and conclusions for theory building in the fields of trust research, technology usage, and health and exercise sciences were provided. Trust in technology was found to be an important aspect to explain fitness app usage, whereas body trusting was not related to trust in technology or with fitness app usage. Therefore, it seems difficult to integrate body trusting into traditional trust theories. This work provided a first approach to identify the role of trust in body trusting, and future studies are needed to elaborate on this in further detail. Furthermore, longitudinal designs are needed to test the causal relations between trust, risk, and benefit, and to gain further understanding of the processes within the trust in technology model.

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1. Introduction

"I measure, therefore I am" (Crawford, Lingel, & Karppi, 2015, p. 486)

Ever since, humans have had an epistemic need to collect trustworthy information and to evaluate their environment (e.g., Sperber et al., 2010; Spink & Cole, 2006). Valid information is a key element to acquire knowledge and to act in an adaptive and reasonable way, and also to reduce risks of diverse nature (Fallis, 2006). In contemporary times, we have become enabled to collect large quantities of information within little time via digital media. *Big* and *Bigger Data* are processed by gadgets that become more efficient at a tearing pace. *Digitalization*, i.e., the transformation of analogue information into digits (Chandler & Munday, 2011), leads to changes in multiple environments, such as living, working, medical care, etc. (Fischer & Pöhler, 2018; Kagermann, 2015; Latos, Harlacher, Przybysz, & Mütze-Niewöhner, 2017). For example, people remote control the heating in their smart homes, replace workflow by robots, use online tools for public services (i.e., e-government), and attend online yoga courses.

Also, digitalization has changed the way and speed people communicate with each other, i.e., the process how information is exchanged between individuals (Blöbaum, 2014; Communication, 2019; Rosa & Scheuermann, 2010). Instead of face-to-face interaction, people use social media, online chats, and online dating platforms to communicate. In many peoples' everyday lives, it has become normal to be permanently online and to be connected with the world wide web (Vorderer & Kohring, 2013). Within the time of a few clicks, we can acquire highly relevant or irrelevant knowledge. We can gather information about the number of deaths after a tsunami in the Pacific Ocean, see what the weather is going to be like tomorrow, or get the latest news about Justin Bieber's mum. We communicate *via* digital media with others—for example via telephones, mails, and chats—and we also communicate *with* digital media. Therefore, the smartphone, computer, etc. have become direct communication partners. In this context, we use digital media to gain information about our environment (e.g., the latest news), but we also use digital media to gain information about *ourselves*, such as our today's step count, blood pressure, mood, or allergy symptoms.

Meanwhile, various smartphone applications (apps) and wearables are offered which track health related parameters, such as covered steps and running distance that measure our physical activity levels throughout the day (West et al., 2012). Thus, these so-called *fitness apps* offer objective information about body-related processes and states. Fitness apps are widely used: specifically, more than a third of the population across western societies stated to have used a fitness app in the past (GfK, 2017). Creating an overarching and interdisciplinary framework model to answer the questions targeted in this study, fitness apps represent a first overlap between the fields of digital communication technology and aspects related to body and health (Figure 1).

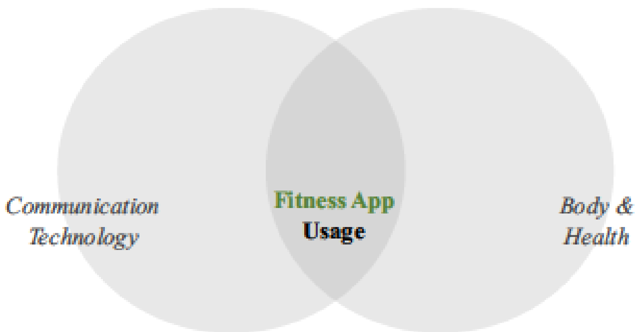


Figure 1. Visualization of fitness app usage as an intersection of digital communication and health.

Fitness apps can contribute to *health behavior*, for example to enhance physical activity and to establish health related routines (e.g., Schoeppe et al., 2016). Beyond the background of increasing levels of severe health problems associated with physical inactivity identified by the WHO (2017), it has become a large interest of health care providers, politics, and scientists to find factors that can positively influence physical activity in the broad population around the world (Wendel-Vos, Droomers, Kremers, Brug, & Van Lenthe, 2007; WHO, 2017). One such easily applicable and low threshold option could be the use of fitness apps. However, high dropout rates in fitness app usage are observed (GfK, 2017). Beyond the background of promising health related *benefits* associated with fitness app usage, it is of high interest to shed light into the process of initiation of and dropout from fitness app usage.

Besides these benefits, fitness app usage can also entail certain *risks* (Figure 2). During usage, highly personal and sensitive data collected by fitness apps are not only processed and stored in our smartphone devices and computers, but also on large external servers. For example, it has been reported that such servers have been illegally hacked in the past (e.g., Barcena, Wueest, & Lau, 2014). The complexity of information collected by the fitness apps comes with a need to reduce information and to extract the most valid of it. Not surprisingly, recent research has indicated that some fitness apps underlie systematic biases in running distance or heart rate estimation, posing risks that can endanger the user's health (e.g., Gorny, Liew, Tan, & Müller-Riemenschneider, 2017).

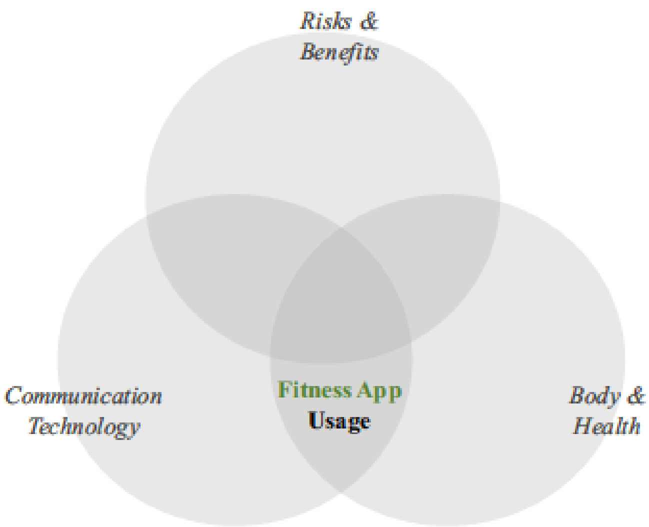


Figure 2. Visualization of fitness app usage as an intersection of digital communication and health, and the integration of *risks* and *benefits*.

The multiple aspects of prevalent risks raise the question of trust: Trust has been identified as an effective form of complexity reduction (Luhmann, 1968), and as the “willingness to take a risk in the relationship and to be vulnerable” (Mayer, Davis, & Schoorman, 1995, p. 714). Thereof, risks and benefits and their implication to consider trust as a key element complement the research framework model of this work. The interdisciplinary research framework model consists of the three core fields of study, i.e., communication technology, body and health, the implication of risks and benefits, and their fields of overlap.

In sum, *trust* emerges as a key aspect when it comes to fitness app usage, its benefits and risks. At this point, new forms of trusting emerge: in its traditional sense, trust was regarded as an interpersonal construct (Lewicki, Tomlinson, & Gillespie, 2006; Luhmann, 1968). In digital times, the traditional concept of interpersonal trust shifts to trust relations between persons *via* digital media, and also to trust relations between persons *and* the media, such as computer programs or the smartphone (McKnight, Carter, Thatcher, & Clay, 2011; Söllner, Hoffmann, Hoffmann, Wacker, & Leimeister, 2012). Thus, new forms of trust arise that are promising to understand mechanisms associated with fitness app usage, representing an overlap between communication technology and risks and benefits (Figure 3): *Trust in technology*.

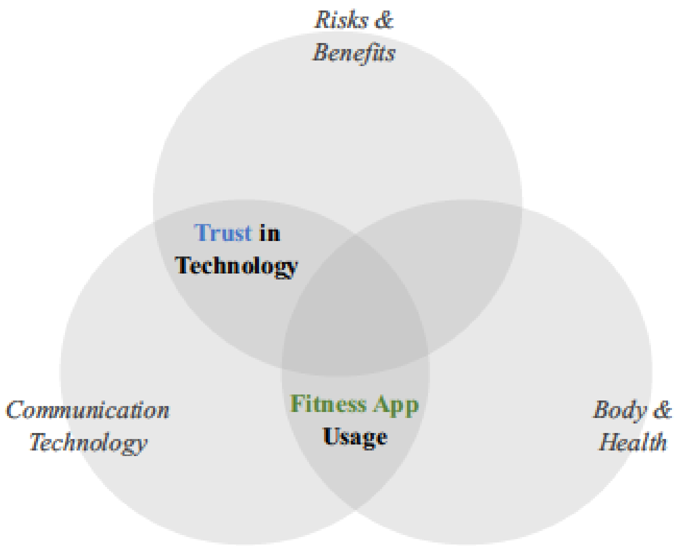


Figure 3. Visualization of fitness app usage and trust in technology beyond the background of risks and benefits.
Note: Trust related variables are marked *blue* and *fitness app* related variables are marked *green* throughout this work to provide a better overview.

Besides health care purposes, fitness apps offer objective information about their user, such as step counts, covered distances, or calorie consumption. Digital media provide a quantification of subjective states that imply objectiveness and appear to be true and trustworthy. People are interested in collecting objective parameters about their body, fulfilling their epistemic need for valid information (En & Pöll, 2016). The reasons why people engage in self-tracking are assumed to be about finding patterns in one's behavior, about causes and trajectories of a disease or unhealthy behavior or physical inactivity (Moschel, 2013). The implication of these issues is that human life is risky. Specifically, these risks can involve physical dysfunction, disease, and also social risks such as failing to meet social norms and standards (En & Pöll, 2016). Furthermore, human perception is based on subjective and biased feelings and memory, being of risk to be untrustworthy. Digital media can provide a tool to produce "hard facts" and a more "objective" reality (En & Pöll, 2016, p.

44). Hence, self-tracking is described as a means to practice *control*, consequently leading to risk reduction.

Meanwhile, large parts of smartphone users regularly track health related parameters to gain insight about their bodies—for health treatment purposes or just for fun. The media and specifically health product providers have contributed to the perception of why self-tracking can be beneficial for us. Specifically, it has been conveyed that self-tracking is of epistemic value and can enhance quality of life. As this desire was shared by numbers of people, a new lifestyle emerged. The lifestyle associated with collecting and tracking body-related data was named the *quantified self* (Nafus & Sherman, 2014; Wolf, 2009). So, to speak, persons can learn about their body states by means of digital self-tracking and specific feedback. Within the past years, the quantified self-movement has become popular, and people started to share their experience with their practice of self-tracking via websites or local groups (Nafus & Sherman, 2014). Within the quantified self-movement, the experience of self-tracking was described as gaining "a fuller experience of what changes in date, such as [how] rising glucose levels might physically feel like. One learns how to feel one's body through the data" (Nafus & Sherman, 2014, p. 1789). Self-tracking was also described as a matter of trusting and calibrating subjective body sensations with objective data provided by the app (Sharon & Zandbergen, 2017), or even as a central aspect of existence, as described by Crawford et al. (2015, p. 486): "*I measure, therefore I am*".

In sum, the objective data provides the recipients with a possibility to control, potentially leading to risk reduction and benefits in health behavior. Furthermore, it has been indicated that self-tracking is of epistemic value and can enhance body knowledge, body trusting, and quality of life. But can self-tracking change the way we experience and trust our body and our body sensations? Can it contribute to higher levels of well-being? Beyond the background of diverse body related risks and benefits associated with self-tracking via fitness apps, a completely novel form of trust emerges, representing an overlap between body and health and risks and benefits (Figure 4): *Trust in the own body*.

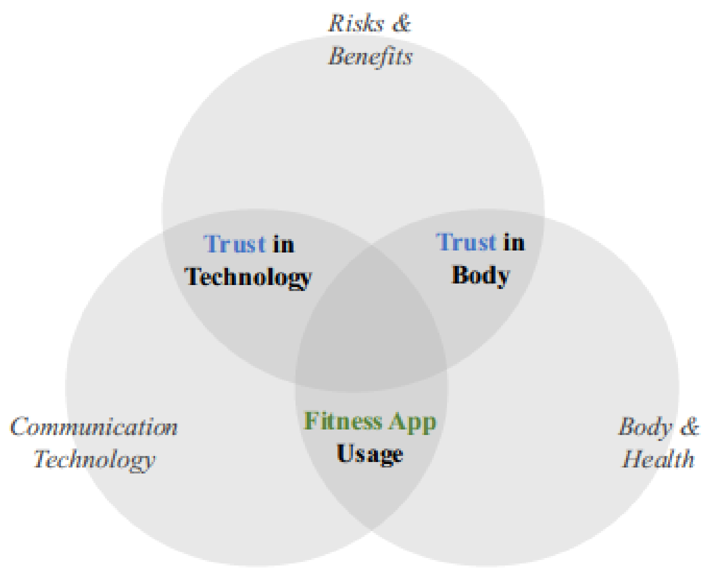


Figure 4. Visualization of fitness app usage, trust in technology, and body trusting beyond the background of risks and benefits.

Overall, diverse aspects of everyday life and health behavior are changing as a trajectory of digitalization, and so do forms of trust. In the context of fitness app usage, both benefits and risks emerge. The importance to consider trust in fitness apps is raised to understand processes of initiation of and dropout from fitness app usage. Furthermore, novel approaches have described self-tracking as a means to enhance body trusting. Beyond the background of trust research, two important aspects of trust are considered: First, trust in technology, and second, trust in the body. Yet, it is unclear whether body trusting can be compiled with traditional models of trust, whether it can be connected with other trust concepts (e.g., trust in fitness apps), and how fitness app usage is connected with body trusting or can influence body trusting.

Hence, overall, the key questions to be targeted are:

(1) How do *trust*, *risk,* and *benefit* perceptions contribute to understanding *fitness app usage*, including the processes of initiation, maintenance, and dropout?

(2) Can *body trusting* be regarded as a novel form of trust? How are *body trusting* and *trust in technology* related to each other and to *fitness app usage*?

(3) Can constant self-tracking *via fitness apps* change a person's *body trusting*?

To answer these overarching and multidisciplinary questions, it is crucial to gain knowledge about trajectories of digital communication and its applications in healthcare, about the development of trust concepts and its application to the technology context. Furthermore, it is important to know how self-tracking via digital media has emerged, how it can potentially change the way people trust their body and whether body trusting can be regarded as a form of trust. Therefore, an integrative and heuristic research framework model is proposed that builds up on the interrelations between digital communication, body and health, and risks and benefits, specifically targeting the interrelations between fitness app usage, trust in technology, and body trusting (Figure 5).

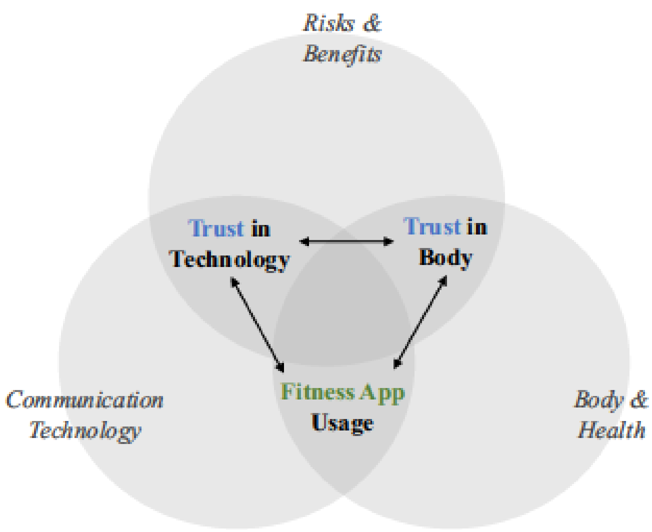


Figure 5. Proposed research framework model to identify the interrelations between fitness app usage, trust in technology, and body trusting beyond the background of risks and benefits.

Hence, in the following, *Chapter 2* focuses on the role of digitalization and digital communication in the present times and how digitalization has entered the health context. More specifically, smartphone health apps and related devices are introduced, shading light onto their benefits and risks. Afterwards, models are presented that have been established to understand and predict technology usage, health app usage, and specific fitness app usage.

Chapter 3 provides an insight into the history and development of trust research, including diverse forms and aspects of trust. Building up on the application of digital media to the health context, Chapter 3 particularly focuses on trust beyond the background of digitalization and technology, and introduces different objects of trust, such as persons, technology, or the own body. Thereof, models are presented that target the understanding of technology usage based on trust concepts. Furthermore, risk and benefit evaluations are key aspects in trust concepts and are especially relevant when trust establishes in new relations, such as with new media (e.g., McKnight et al., 2011). Hence, models describing associations between trust, risk, benefit, and control are presented.

Chapter 4 focuses on the practice of self-tracking via fitness apps. Overall, Chapter 4 brings together both aspects of digital technology that are designed to enhance health behavior introduced in Chapter 2, and the application of trust models introduced in Chapter 3. First, special characteristics of self-tracking via digital media are outlined, laying a focus on its risks and benefits. Then, the *quantified self*—a lifestyle associated with self-tracking—is introduced, which has been assumed to promote body trusting. In this context, a theoretical foundation of *body trusting* is presented. Consequently, body trusting arises as a potentially novel form of trust, synergizing the key points targeted in this work.

Chapter 5 brings together the contents of the three overarching areas of communication technologies, body and health, and trust that were introduced through the

Chapters 1-4. Based upon these aspects and intersections of the areas, a research program is established that is guided by the heuristic research framework model introduced in this work. Specifically focusing on the relations between fitness apps, trust in technology, and body trusting, the assumed relations between the variables are targeted.

Chapter 6 provides a presentation of the three empirical studies and diverse analyses included in this work. Therefore, each a brief study specific introduction is provided, followed by the methods, results, and study specific discussion sections. Some of the studies entail diverse parts that are partly based on the analysis of subsamples (e.g., fitness app users, non-users, and dropout), with the aim to elaborate on the processes of initiation of, maintenance of, and dropout from fitness app usage.

Chapter 7 provides a general discussion of the results found in Chapter 6 that is presented beyond the background of the theoretical foundation that had been outlined throughout the Chapters 1-4. Furthermore, implications for theory building and practice-relevant implications for safe and healthy fitness app usage are provided. Finally, the results found in this work are integrated into the heuristic research framework model that guides through this work.

2. Digitalization

Digitalization and the use of digital technology have become central and important elements of our professional and everyday lives. Thus, first, general definitions of digitalization and digital communication are provided in this chapter. The role of digitalization in the present times is described, showing the development of technology usage in everyday life and the use of digital communication. Afterwards, the specific usage of smartphones and related applications is targeted. In a next step, it is presented how digitalization has been applied to the health context, yielding to the specific field of smartphone apps and fitness apps. In this context, both the benefits (e.g., enhancement of physical activity) and risks (e.g., data security) associated with fitness apps are presented. As technology usage and fitness app usage are important and beneficial tools in everyday life, models describing and explaining technology usage and app usage are outlined. In this context, specific scientific results are presented identifying factors associated with fitness app usage. Thus, Chapter 2 sheds light onto the fields of communication technology and their application to body and health, and their overlap, representing fitness app usage (Figure 6).

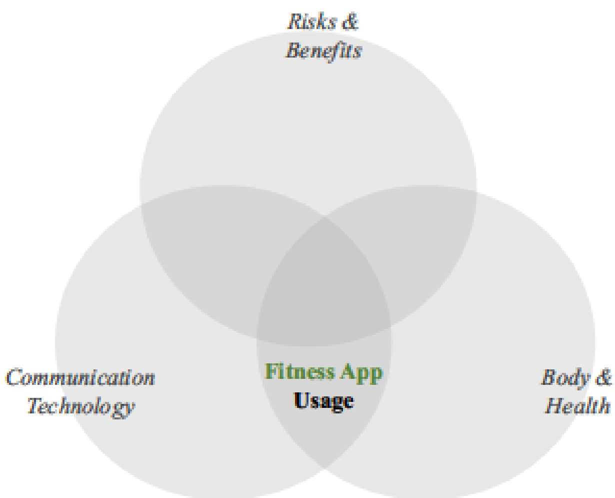


Figure 6. Visualization of fitness app usage as an intersection of digitalization and health and the integration of risks and benefits targeted in this Chapter 2.

In its basic sense, digitization is defined as the transformation of analogue information into digits, i.e., into zeros and ones (Chandler & Munday, 2011). To handle and process digital information, programmable devices (i.e., information technology; IT) are used by human beings, and also to control machines (Boaden & Lockett, 1991; Lee & See, 2004). Digitalization is based on digitization, describing the digitized aspects of technologies that can be integrated into the everyday life (Gray & Rumpe, 2015).

Digitalization has become important in diverse aspects of everyday life and professional contexts (Gray & Rumpe, 2015). In scientific research, scientists can digitize their results and analyze these via sophisticated statistical methods. Furthermore, scientists can make their data available on the internet, authorizing transparency and the possibility for replication. In business, information about companies' sales can be integrated to derive complex calculations of trajectories and changes at the stock exchange. Also, multiple applications of digitalization are possible in everyday life. For example, smartphones provide the opportunity to connect to the internet and to receive information within a short time. Smart home systems make it possible to manage music and the television via a remote control, or even to control the house's heating via the smartphone (Chan, Campo, Estève, & Fourniols, 2009; Gray & Rumpe, 2015). Commerce and sale in both professional and everyday contexts shift from analogue to digital processes (i.e., electronic commerce; e-commerce). More sophisticated applications of the internet enable users not only to consume internet content, but also to actively contribute to the web content. One example is the upload function of social networks that can be used to share a person's experiences. The interactive contribution of personal contents to the internet has been defined as the *web 2.0* (Davis, 2012). Sophisticated systems have also been adapted to healthcare, contributing to the development of the electronic healthcare (e-healthcare). For example, portable systems exist in e-healthcare that measure the blood glucose level in patients suffering from diabetes. These systems also automatically adapt the correct doses of needed insulin, and therefore contribute to safe and high quality healthcare (e.g., Rollo et al., 2016). Overall, digitalization has enabled people to process large quantities of data, which is also labelled as *Big Data*.

Big Data is a term that has been widely used across disciplines, and also in anecdotal contexts (Ward & Barker, 2013). Therefore, the descriptions of Big Data in anecdotal context often lack of concrete and specific definitions. According to Ward and Barker (2013), Big Data refers to two aspects: (1) storage of data; and (2) analysis of data. In particular, "big" indicates high levels of quantity, complexity, and significance. Another definition of Big Data involves the three "V"s; (1) high *volume* of data; (2) high *velocity* of data; and/or (3) high *variety* of data (Big Data, 2019). Therefore, Big Data "enables enhanced insight, decision making, and process automation" (Big Data, 2019).

In sum, digitalization is a means to condense data and to make it more easily available. Large amounts of analogous data, such as scientific measurements, become available and analyzable. By means of digital tools, large data sets can be integrated into clearly arranged results. Chandler and Munday (2011, p. 1) describe this result of digitalization as a "model of the world that it describes" and as "artifacts of the real world".

At the same time, however, the large amount of available data cannot contribute to knowledge formation in its raw form. Specific relevant information needs to be extracted from the irrelevant information and needs to be abstracted to gain information and knowledge. Therefore, strategies to reduce complexity are needed. One mechanism to reduce complexity is trusting others (e.g., Luhmann, 1968), which is targeted in Chapter 3.

2.1 Digital Communication

Digitalization has changed the way information is exchanged and how people communicate (Kagermann, 2015; Latos et al., 2017; Rosa & Scheuermann, 2010). In general, communication is defined as the "process by which information is exchanged between individuals through a common system of symbols, signs, or behavior" (Communication, 2019). Applied to the digital context, digital media can function as means to convey information. Digital communication can refer to content that is inherently analogue (e.g., speech or behavior), and can also refer to content that is inherently digital (e.g., statistical results, text files; Lee & Messerschmitt, 2012). For the purpose of digital communication, analogue information needs to be transformed into digital information. Therefore, the continuous analogue information (e.g., speech) is sampled and converted into a digital signal by an analogue-to-digital converter (A/D; Figure 7). Next, the bit stream is transferred via a digital transmission system and re-converted via a digital-to-analogue (D/A) converter and reconstructed via a reconstruction filter. In sum, an abstraction of the analogue reality is created, which can also be object to errors, and can create risks.

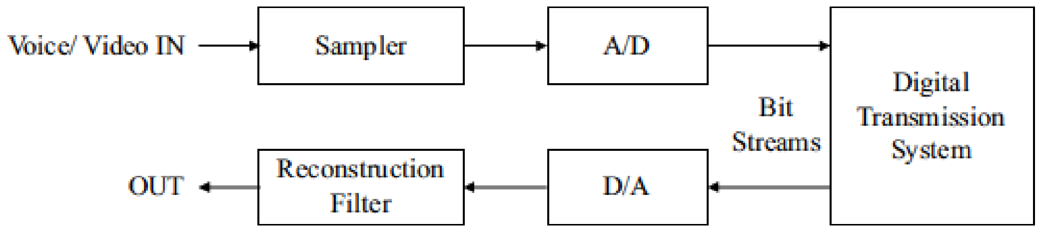


Figure 7. Visualization of an analogue to digital transmission system, adapted from Lee and Messerschmitt (2012).

During the times of digitalization, the speed of communication has increased, and so have technological, economic, social, and cultural processes (Gleick, 1999; Latos et al., 2017; Rosa & Scheuermann, 2010). Modern technologies (e.g., computers) make it possible to exchange information within seconds or milliseconds without the requirement of personal contact. One important means that enables people to communicate in nearly real time is the smartphone.

2.1.1 Smartphones. Smartphones are "mobile communication devices that use identifiable operating systems" (Smartphones, 2019). According to Statista (2018), the connected device usage rate had increased from 50% in 2014 to 75% in 2017 in Germany, and has become as important and as frequently used as the computer in 2017. Furthermore, the smartphone usage rate has increased from 44.65% in 2014 to 67.11% in 2017 and is estimated to further increase up to 78.59% in 2022 (Figure 8).

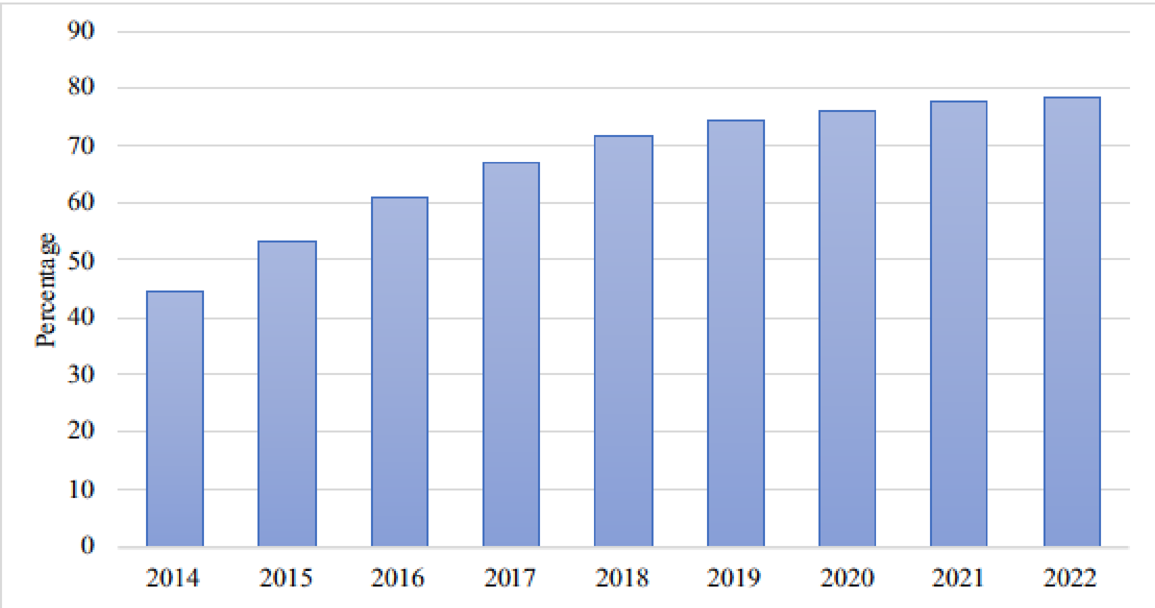


Figure 8. Smartphone usage rate in Germany from 2014 to 2017 and forecast from 2018 to 2022, adapted from Statista (2018).

In 2016, 17.3% of Germans used the internet on their smartphone for longer than 120 minutes per day. Consequently, the smartphone has become one of the most popular and widely used communication device within the past decade. Meanwhile, sophisticated smartphone-based systems have been established, such as smartphone-based vehicle communication via internet that can contribute to automatic driving in cars (Abid, Chung, Lee, & Qaisar, 2012).

2.1.2 Smartphone applications. On a smartphone, third-party applications can be installed and removed, and the user interface provides simultaneous usage of applications (apps). Smartphone apps are specifically designed to run on a smartphone, and are available in online app stores (West et al., 2012). They have become available since the launch of Apple's App Store in 2008. Some apps are free of charge, some apps need to be paid, and some apps contain implemented in-app pay options to install upgrades. In 2018, the average app price across all apps was 1.02 U.S. dollars (Statista, 2018). Since the launch of app stores in 2008, the number of downloads has increased in a j-shaped form. In July 2009, a total of 1.5 billion apps had been downloaded from the Apple App Store, in October 2013 60 billion apps had been downloaded, and in June 2017 180 billion apps had been downloaded (Figure 9).

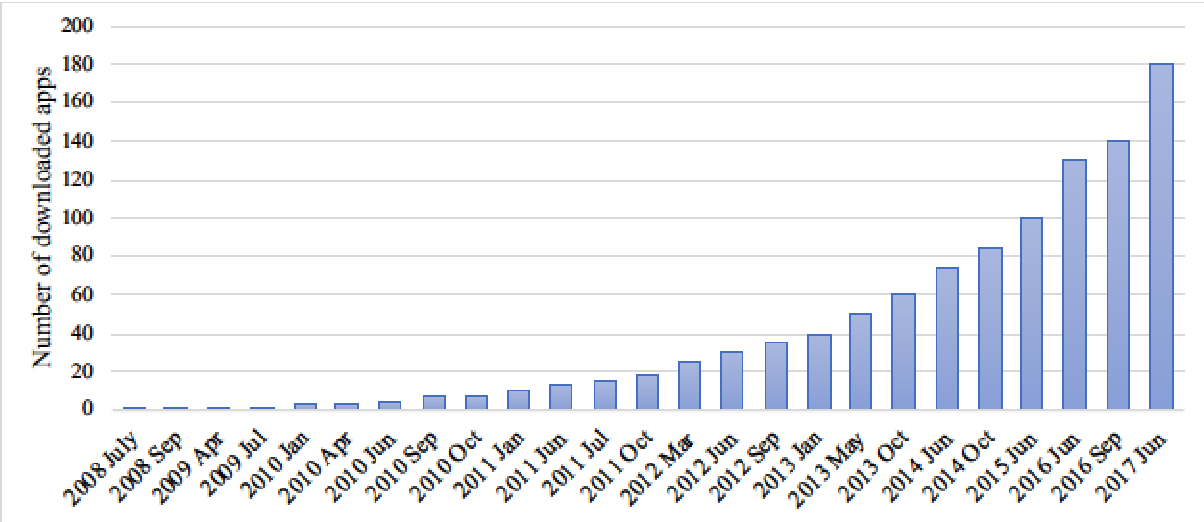


Figure 9. Cumulative number of apps in billions downloaded from the Apple App Store, adapted from Statista (2018).

The overall number of mobile app downloads was 178.1 billion per year in 2017. The annual number of mobile app downloads is estimated to increase to 205.4 billion downloads in 2018 and 258.2 billion downloads in 2022. Thus, smartphone apps are of low cost and have been increasingly used within the past years. Smartphone apps are designed for diverse purposes. As presented in Figure 10, the most popular app store categories worldwide in 2018 were games (24.86%), followed by business (9.77%), education (8.5%), and lifestyle (8.32%) (Statista, 2018).

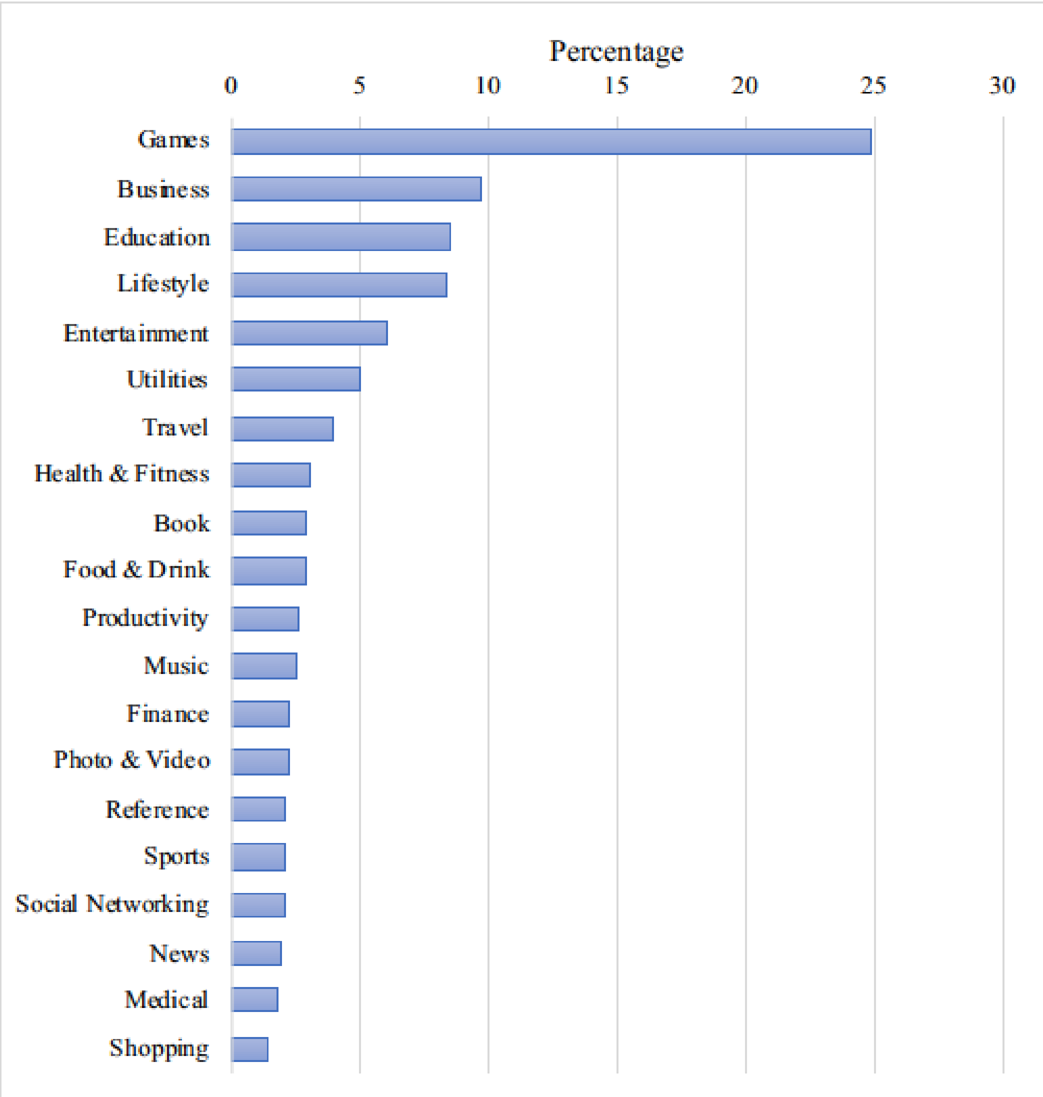


Figure 10. The most popular Apple App Store categories in September 2018, adapted from Statista (2018).

In sum, smartphone apps are low-cost, have become increasingly popular, and are estimated to increase in popularity within the next years. Therefore, smartphones are a promising means that also can provide support in everyday life or enhance desired behavior, such as health behavior.

2.2 Digitalization and Health

Smartphone usage has been widely adopted and has created the opportunity for large frequency interaction (Statista, 2018). Therefore, health practitioners have become interested in implementing health behavior related options and gadgets (Riley, Lee, Cooper, Fairburn, & Shafran, 2007; West et al., 2012), leading to the establishment of electronic health (*e-health*) and mobile health (*m-health*). E-health refers to electronic gadgets that are used in health context (e.g., including electronic insulin measurement). M-health refers to health-related applications that are specifically used on mobile devices, such as smartphones. The first m-health applications referred to simple message systems (SMS) that were mainly related to diabetes management or smoking cessation (Fjeldsoe, Marshall, & Miller, 2009). After the first smartphone apps had been provided in 2008, options for more sophisticated applications and interfaces emerged, opening the market for apps that were designed to influence health behavior.

2.2.1 Health apps. Health apps are related to the category of lifestyle apps and are ranked number four of the most downloaded applications worldwide (8.32%; Statista, 2018). Within the category of paid health apps, West et al. (2012) conducted a content analysis and used categories based on the Health Education Curriculum Analysis Tool (HECAT; U.S. Control & Prevention, 2007), as presented in Figure 11. According to their analysis, the most frequent health apps were related to physical activity (33.21%), followed by personal health and wellness (28.84%), healthy eating (19.51%), mental and emotional health (12.41%), sexual and reproductive health (7.28%), alcohol, tobacco, and other drugs (3.93%), and violence prevention and safety (2.88%).

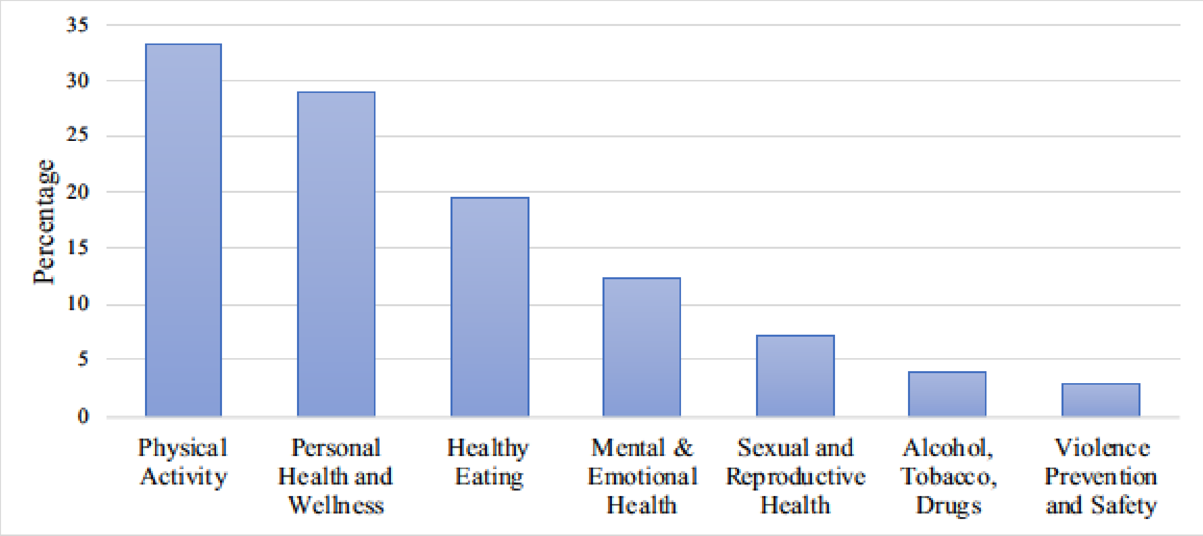


Figure 11. The percentage of the most frequent health app categories, adapted from West et al. (2012).

Most of the apps cost less than one dollar (42.30%), 23.77% cost between one and three dollars, and 33.93% cost more than three dollars. In comparison, higher priced apps (exceeding one dollar) were rated more likely to promote health or to prevent disease and were rated more trustworthy and credible at being capable to promote health or prevent disease, pointing a first indicator to the matter of trusting in health app usage.

2.2.2 Health apps and physical activity. A broad range of health apps has been designed to implement health related behavior on the field of physical activity (West et al., 2012). Over the past decades, overweight and obesity have increased and have been found to be highly prevalent. Overweight is indicated at a body mass index (BMI; a calculation of body weight in kg divided by the squared body height in meters) that is greater than or equal 25, and obesity is indicated from a BMI greater than or equal 30 (WHO, 2017). Based on recent data, 68% of adults in the United States, and 57% of adults in Germany are overweight, and overall about 13% of the world's adult population was found to be obese in 2016 (WHO, 2017). Furthermore, the worldwide prevalence of obesity nearly tripled between 1975 and

2016. In Europe, overweight has increased from 56.5% in 2006 to 62.3% in in 2016 (WHO, 2017).

Overweight is associated with an increased risk of multiple diseases, such as heart diseases, type-II diabetes, and high cholesterol levels (Field et al., 2001; Prugger & Keil, 2007; WHO, 2017). Furthermore, a j-shaped relationship between BMI and the relative risk of death was found, indicating severe physical risks in overweight persons (Prugger & Keil, 2007). In prevention of both chronic physical and mental diseases such as diabetes type two, hypertension, and depression, physical activity has been identified as an important predictor of health status (Warburton, Nicol, & Bredin, 2006; WHO, 2017). Prevalence of overweight and obesity have also been shown to be associated with lower socioeconomic status (Helmert & Strube, 2004), raising the need to implement low-cost and low-threshold options targeting overweight in the broad society.

The main factors causing overweight and obesity are considered to be an increased physical inactivity and an increased intake of high caloric food (WHO, 2017). Therefore, the support of physical activity in large segments of the population is one major goal of global policies and health research. To enhance physical activity, researchers have investigated different facilitating factors at the individual, social, and policy level (Teixeira, Carraça, Markland, Silva, & Ryan, 2012; Wendel-Vos et al., 2007).

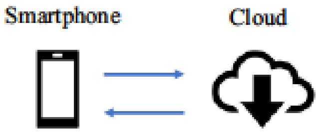
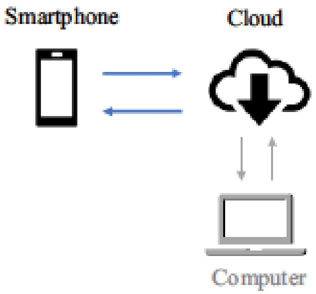
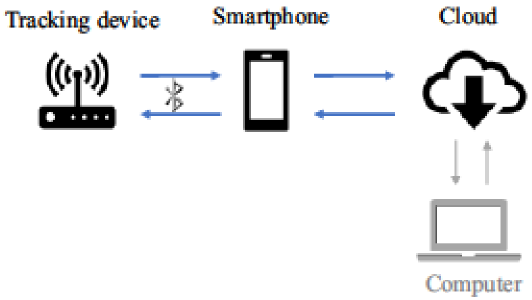
With the aim to reduce epidemiologic problems associated with overweight and obesity, it has been recommended that people engage in moderate exercise of about 150 minutes per week in units of at least ten minutes, for example five times a week for 30 minutes (Warburton, Charlesworth, Ivey, Nettlefold, & Bredin, 2010), and an additional of 75 minutes of vigorous-intensity (Bouchard, Blair, & Haskell, 2012). Likewise, coverage of 10,000 steps per day are recommended (Bouchard et al., 2012; Tudor-Locke, Brashear, Johnson, & Katzmarzyk, 2010). However, results of studies investigating physical activity via accelerometers in western societies indicate that only 15% of Canadian adults and 5% of US adults meet these recommendations (Colley et al., 2011; Matthews et al., 2008). In Germany, such large observational studies are yet to be conducted.

2.2.3 Fitness apps. Fitness apps are a current trend and are designed to support physical activity in daily life (Poushter, 2016; West et al., 2012). The first fitness apps emerged in 2008 when GPS trackers became small enough to fit in a mobile phone (Crawford et al., 2015). Fitness apps use a range of technologies implemented in the smartphone or a wearable that are designed to track a person's physical activity. The measured activity can refer to the start and end times, the speed, location, route, and altitude of a course. Fitness apps often use combinations of the smartphone's positioning system, microphone, camera, and accelerometer to collect and integrate data (Higgins, 2016). Consequently, the precision of the measurement is limited by the smartphone's technical capabilities. With regards to devices used to collect and handle the data, there is a range of options that have been established (Table 1).

First, the data collected by the smartphone can be analyzed and stored on the smartphone. It is usually required to allow the collected data to be synchronized to a cloud. In the cloud, additional and more sophisticated analyses can be run (e.g., calculation of calorie consumption over a time span). *Second*, the data and results can then be downloaded via the smartphone or a computer that is connected to the internet. *Third*, wearable devices exist that can be worn on the body that generate data and that connect to the smartphone app.

Table 1

Tracking System Models

Tracking System Model	**Description**	**Visualization**
1. Smartphone app and cloud	A smartphone collects and analyzes data. The data is synchronized to a cloud for more sophisticated data analysis.	
2. Smartphone app, cloud, and computer	Additionally, the data stored in the cloud can be accessed via a user account on the local computer, the smartphone, etc.	
3. Wearable, smartphone app, and cloud	A wearable device collects data and transfers it to the smartphone app via Bluetooth etc. The data is processed by the app, the cloud, the device, or a combination of the three. The data can also be accessed via an account on the computer.	

Note. Grey, optional synchronization with an online account on the computer.

2.2.3.1 Fitness app devices. Fitness apps also come with an option to connect with a wearable device, usually via a wireless Bluetooth function. To date, a variety of gadgets exist, ranging from small accelerometer applications to wristbands, belt sensors, smart watches, or even smart clothing that come with implemented sensors (Zheng, Ding, & Poon, 2014). Depending on the gadget, it is also possible to track the user's heart rate, sleep, movements, etc. Many fitness app providers offer wearable wristbands that come with an inbuilt accelerometer and that can recognize different forms of activity or inactivity, such as running, biking, cross-trainer, and also sleeping. Some wristbands have small lights implemented that indicate the activity progress. More sophisticated and expensive wristbands often include a watch-like display and an assessment of the heart rate. Most wearable wristbands are waterproof and have an inbuilt option to recognize and track swimming activity. Also, most fitness apps provide an estimation of the calorie consumption that is based on the physical activity data that is gathered via the device. Across functions and wearable providers, these gadgets vary in reliability, accuracy, and quality (Dooley, Golaszewski, & Bartholomew, 2017; Gorny et al., 2017; Kaewkannate & Kim, 2016). For example, some gadgets were found to underlie systemic over- or underestimation of the heart rate or the step count, and therefore pose potential risks to the user.

Often, the tracking devices neither contain an interface for adequate data presentation and management. Nor do they provide the technical requirements for data analysis and storage. Therefore, most wearables constantly synchronize with the smartphone app to provide the user with formatted and convenient output (Table 1).

2.2.3.2 Fitness app functions. A diversity of functions can be implemented in fitness apps. Reviewing 19 fitness apps, Higgins (2016) identified the most popular functions: $n = 17$ apps provided exercise monitoring, $n = 16$ apps had an option to connect with social networks, $n = 14$ apps had an option for tailored feedback, $n = 10$ apps provided goal setting,

$n = 9$ apps provided audio cues, $n = 8$ apps had an option for diet monitoring, $n = 7$ apps had a virtual coaching implemented, and $n = 2$ provided sleep monitoring (Figure 12). Synchronization with other apps was possible in $n = 8$ apps, and synchronization with other gadgets was possible in $n = 7$ apps.

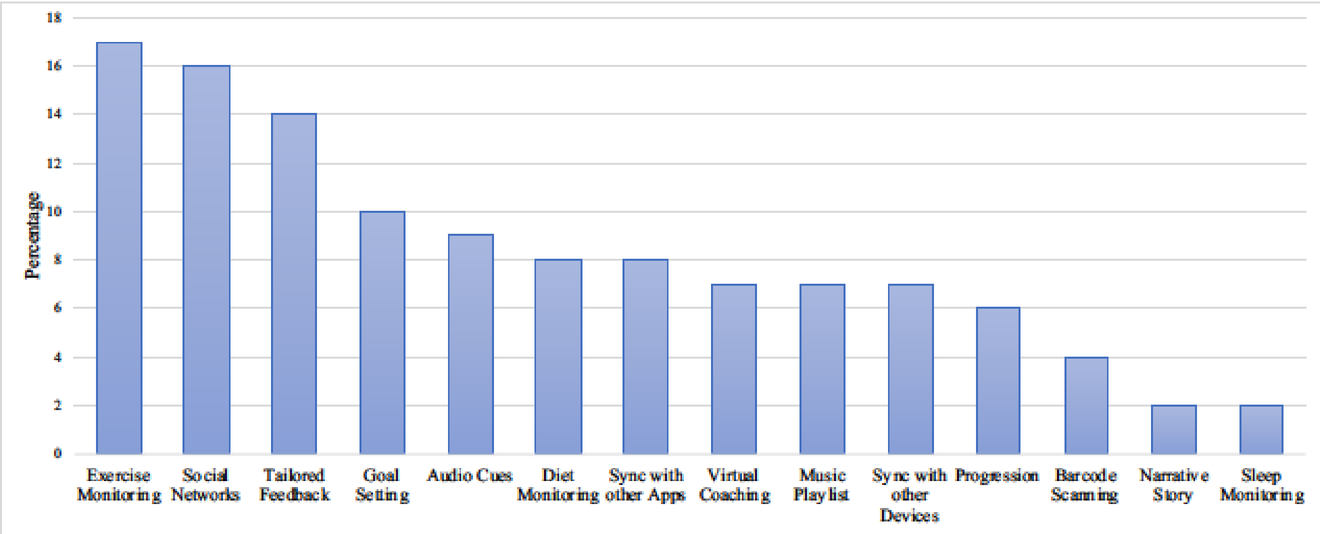


Figure 12. Most popular app functions reviewed by and adapted from Higgins (2016).

Fitness apps are the most popular and widely used apps on the health app sector, representing 33.21% of the reviewed health apps (West et al., 2012). Furthermore, fitness app usage has experienced a rapid growth (Barcena et al., 2014). Within the first six months of 2014, a 62% growth in the use of health and fitness apps was observed. Yet, the most popular fitness app is used by up to 50 million users (Barcena et al., 2014). In an international comparison, 33% of the respondents stated to currently monitor or track their health or fitness via an app, fitness band or smartwatch in average across all countries (GfK, 2017). Specifically, 45% of Chinese, 29% of U.S., 28% of Germans, 19% of Britons, Canadians, and Australians, and 13% of Dutch stated to currently track their fitness (Figure 13).

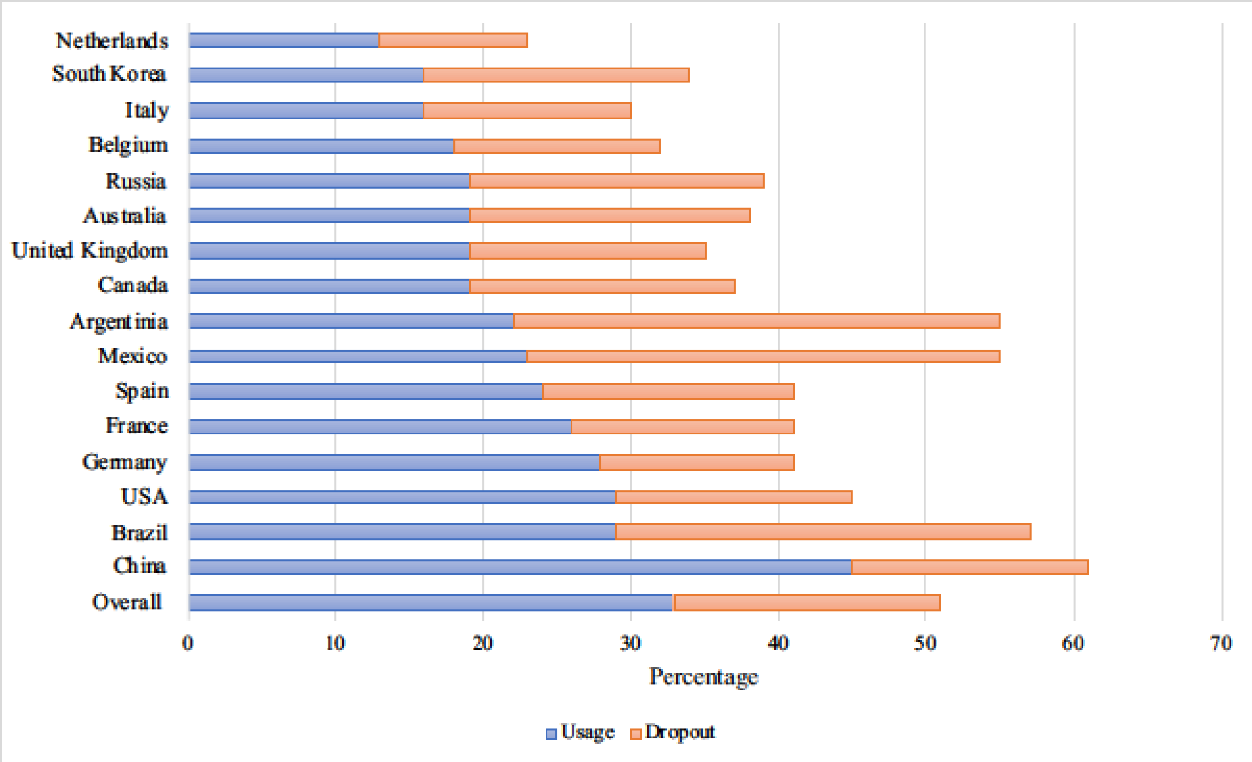


Figure 13. Percentage of people stating to currently track their physical activity or health (*Usage*) or to have tracked their physical activity or health in the past (*Dropout*), adapted from GfK (2017).

The participants of the survey (GfK, 2017) stated to track their health or fitness in order to maintain/improve fitness (55%), to motivate themselves to exercise (50%), to lose weight (29%), because it is fun (22%), or to compete with other people (8%).

Fitness apps are offered free of charge or as paid versions. Within the paid apps targeting physical activity, further differentiation was provided by West et al. (2012), as presented in Figure 14.

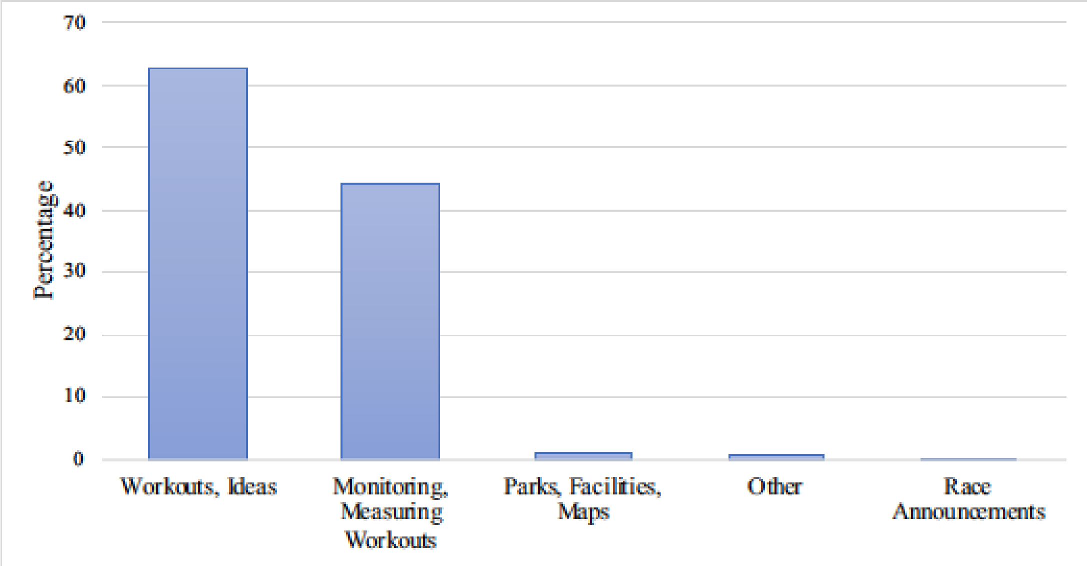


Figure 14. Percentage of services provided in fitness apps, adapted from West et al. (2012).

Most reviewed fitness apps provided workouts, tips and ideas (62.82%), followed by monitoring, measurements of workouts, logs, and automatic recording (44.40%), information about parks, facilities, and maps (0.99%), and race announcements and events (0.09%).

Overall, fitness apps have been designed and used for behavior change, for example to enhance physical activity. Therefore, mainly the Self-Determination Theory (Deci & Ryan, 1985), the Transtheoretical Model (Prochaska & Velicer, 1997), or the Social Cognitive Theory (Bandura, 2001) were used to explain behavior change, as reviewed by Schoeppe et al. (2016). In this context, specific features targeting behavior change such as performance measurement, individual feedback, and goal setting have been implemented in fitness apps. These features have also been associated with larger effectiveness (Conn, Hafdahl, & Mehr, 2011; Direito et al., 2014). On the field of goal setting, the implementation of a daily step target has been applied by many fitness app providers. Following the recommended levels of physical activity (Tudor-Locke et al., 2010), many wearable providers have implemented a pre-defined option for a target of 10,000 steps per day in the app settings. However, researchers have recently discussed adjustments of the step target across contexts and age groups, e.g., in older adults or unhealthy populations (Ayabe et al., 2008; Rowe, Kemble, Robinson, & Mahar, 2007).

2.2.3.3 Benefits of fitness app usage. The investigation of the effects of fitness apps and its specific functions has recently become popular in sport and exercise psychology (Schoeppe et al., 2016). The effects of fitness app usage have mainly been investigated beyond the background of behavior change theories to assess the outcomes on physical activity, dietary intake, and sedentary behavior (e.g., Choi, Lee, Vittinghoff, & Fukuoka, 2016; Goodyear, Kerner, & Quennerstedt, 2017; Maher et al., 2015). It has been shown that fitness app usage can foster higher activity levels, for instance, step counts (e.g., Glynn et al., 2014; Goodyear et al., 2017; Stawarz, Cox, & Blandford, 2015). Reviewing the efficacy of interventions based on fitness apps, Schoeppe et al. (2016) found health improvements (i.e., weight status, fitness, blood pressure) in 14 out of 21 studies targeting physical activity. In seven out of 13 studies targeting diet, and in two out of five studies targeting sedentary behavior, health improvements were found. Multi-component interventions were more effective compared to stand-alone app interventions. Also, multi-component apps (e.g., using pedometers), were more effective than single-component interventions. Interventions using behavior change techniques such as goal setting, rewards, or performance feedback were more effective compared to interventions using no such techniques. Furthermore, it has been indicated that fitness app usage can contribute to habit formation (Stawarz et al., 2015). However, only two of the reviewed studies targeted the outcomes of quality of life such as psychological well-being in secondary analyses. In both studies (Glynn et al., 2014; Maher et al., 2015), no improvements in psychological well-being were found during a fitness app intervention.

In sum, fitness apps can be promising means to enhance physical activity and health behavior. However, the outcomes of fitness app usage on mental states and mental health (i.e., the evaluation of and attention to body states, psychological well-being) have yet to be focused as main research questions. Also, Schoeppe et al. (2016) concluded that it would be necessary to examine the effects of specific app functions under controlled conditions as for example examining effects of external goals implemented in the fitness app.

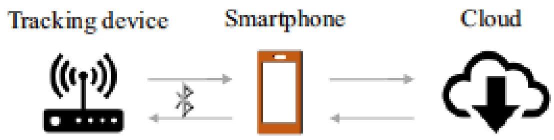
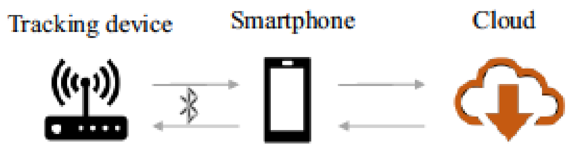
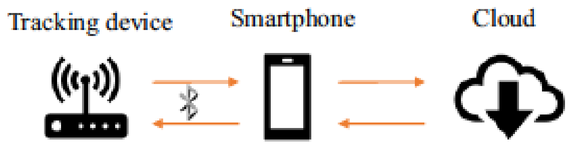
2.2.3.4 Risks of fitness app usage. Besides the positive effects of fitness app usage, researchers have also identified a range of potential risks that emerge for all users, users of specific apps, or users with specific predispositions. One widely discussed risk that is associated with fitness app and general app usage is the risk of data insecurity and the loss of privacy. Reviewing 150 apps in m-health context, Scott, Richards, and Adhikari (2015) identified privacy issues, poorly protected consumer data, data security breaches, lack of app standards and guidelines, and cloud storage as main factors of insecurity in m-health applications. Fitness apps collect a wide range of highly private data, and often ask their users to provide their full name, dates of birth, payment and contact details. Furthermore, people generate and store highly private data such as location details, health and health behavior, or even sexual behavior (Barcena et al., 2014). The collected data can be of high interest for advertisers and cyber criminals.

The emerging risks range from identity theft to profiling, stalking, embarrassment, and corporate misuse (Barcena et al., 2014; Huckvale, Prieto, Tilney, Benghozi, & Car, 2015; Mense, Steger, Sulek, Jukic-Sunaric, & Mészáros, 2016). Data collected via fitness apps is of elevated value for criminals as it includes highly complete data sets that can be used to create credible fake accounts. Also, the comprehensive health related data is of interest for corporate use and misuse, for example for health insurance companies. It has been discussed that health insurance companies use self-tracking data to discount active persons (En & Pöll, 2016). With regards to the location tracking, people become prone of being stalked, for example to criminals who intent to break into their homes. Furthermore, some countries allow the police to use tracking data to detect the average speed and to catch speeding drivers (Barcena et al., 2014). Last, leakage of highly private data such as sexual or toilet behavior can involve high levels of embarrassment and extortion.

Overall, most tracking systems involve three stages that can be potential targets of violated data insecurity: (1) on the device; (2) in the cloud; (3) during data transmission (Table 2).

Table 2

Location of Potential Risks Associated with Fitness App Usage

Data Custody	**Description**	**Visualization**
1. On the device (storage)	Data stored on the device is at risk of being stolen by malware. Especially unencrypted data is prone to this. Also, theft of the device is a potential risk.	
2. In the cloud (storage)	The data stored in the cloud is at risk of being hacked by cyber criminals.	
3. In transit (transmission)	The data transferred from the app or the device to the cloud can be target of traffic sniffing. Especially unencrypted transfer is at risk of being misused.	

Note. Orange, visualization of the location prone to risks associated with data safety.

First, theft of information on the device has been identified as one of the main risks in app usage, accounting for 28% of the threats (Barcena et al., 2014). Weak access control including passwords are of relevance here. Furthermore, insecure data encryption implemented by the app providers can pose a risk of data theft. Additionally, the device can simply be stolen. *Second*, data stored in the cloud is of risk of being stolen. User data are of high interest as they include personally identifiable information and often also payment card data. This information is prone to hacker attacks. *Third*, during transmission, flaws of Bluetooth or Wi-Fi connections and weak encryptions make users vulnerable to traffic sniffing.

A systematic review on the field of health and wellness apps indicated that 89% of the apps transmitted information to online services, no app encrypted personal information that was stored locally, 66% of the apps that sent identifying information via the internet encrypted the data, and 20% of the reviewed apps had no privacy policy (Huckvale et al., 2015). Two out of the reviewed apps were of acute risk for potential data theft by third-parties. Furthermore, fitness app users make themselves vulnerable by allowing the app to access information and in-app purchases. In particular, users have to allow the app to access identity information, location information, contacts, camera, microphone, and Bluetooth information which is often obligatory for usage (Mense et al., 2016). Mense et al. (2016) also found that 80% of the free mobile applications contact third-party websites for advertising and analytics purposes, and one of the analyzed applications sent fitness activity data in plain text to third-party advertisers. 30% of the analyzed apps sent the device ID to the app developer's website which enables the app developer to track the user's activities. Additionally, the authors could prove that a fitness app provider used the user's personal contacts to extract e-mail addresses. In an analysis of m-health and fitness apps, it was found that 85% of the communication between the user's smartphone and the developer's website was not encrypted via SSL (Njie, 2013). Furthermore, 20% of general tracking apps that were not limited to the health context, transmitted user login credentials in clear text (Barcena et al., 2014). Further risks are implied by the systematic estimation bias of measurements (e.g., distance covered, heart rate, step count, calorie consumption) that has been found in a range of devices (Gorny et al., 2017; Kaewkannate & Kim, 2016). In this case, potential risks emerge when users use the body related data to adjust their exercise or dietary behavior on the basis of calorie calculations or draw implications to their health status on the basis of their heart rate. Also, providers of wearable devices present little about *how* they aggregate, calculate, and edit the data collected by the device, for example when it comes to calorie consumption (Crawford et al., 2015). Due to the lack of transparency in how the app and app provider handle and process their personal data, the user is prone to potential risks of receiving incorrect data (such as incorrect calculations of calorie consumption). Beyond this background, the need to trust is raised.

Furthermore, fitness app usage can pose psychological risks to specific user groups. However, only few studies have provided evidence in this field yet. Recently, it has been discussed that fitness app usage, and specifically calorie tracking is selectively used by persons with eating disorder behavior, and can also contribute to manifestations of eating disorder symptoms (Eikey & Reddy, 2017). In a clinical sample, a calorie tracking app was found to be used by 75% of the participants (Levinson, Fewell, & Brosof, 2017). Furthermore, 73% of these participants stated that this app had contributed to their eating disorder. Simpson and Mazzeo (2017) investigated a healthy sample and found that regular fitness tracking was a unique predictor of eating disorder symptomatology and was related to eating disorder attitudes and behaviors. Furthermore, calorie tracking was associated with eating concern and dietary restraint.

With regards to the social media function that is implemented in many fitness apps, it has been demonstrated that neuroticism, extraversion, and conscientiousness can have effects on compulsive usage of mobile social applications (Hsiao, Lee, Chiang, & Wang, 2016). However, there are no studies targeting compulsive behaviors that are connected with fitness app usage to date.

Overall, it has been demonstrated that fitness app usage is associated with a range of beneficial effects, such as enhancement of health behavior and physical activity. However, fitness app usage can also include risks with regards to certain apps and user groups, especially in the field of data security. Thus, it is of high interest to understand the processes that are associated with adoption, maintenance, and dropout from fitness app usage to support longer duration and enhancement of healthy, safe, and beneficial fitness app usage. In doing so, the application of established models describing and explaining both general and technology specific usage is a promising method.

2.3 Technology Usage

General technology and technology usage have become important and beneficial in everyday life and professional contexts (Agarwal & Prasad, 1998; Bassellier, Reich, & Benbasat, 2001). Technology usage not only provides benefits to the user, but non-usage can even involve risks: If a person refuses to use a technology in professional context, this might endanger a company's competitive survival (Agarwal & Prasad, 1998). Thus, it has become of interest to examine the acceptance and adoption of technology.

2.3.1 Technology Acceptance Model. The Technology Acceptance Model (TAM; Davis, 1989) was one of the first models established to explain why people accept or reject information systems and IT. The TAM is to date the most widely used model to explain this relation (Gefen & Straub, 2000; Marangunić & Granić, 2015; Taylor & Todd, 1995). The TAM is rooted in the Theory of Reasoned Action (TRA; Ajzen & Fishbein, 1980), which outlines the prediction of social behavior based on attitudes and social norms, leading to intentions, and to actual behavior. The TRA is also described in more detail in Chapter 3. In the first conceptualization of the TAM (Davis, 1989), perceived usefulness and perceived ease of use were defined as technology related beliefs. Together, perceived usefulness and ease of use lead to the attitude toward using, behavioral intention to use, and the actual system use

(Figure 15A). The beliefs about the technology are influenced by a range of external variables, such as organizational factors, the development process, the task, etc. However, the description of these external variables stays inexplicit and non-specific to the context.

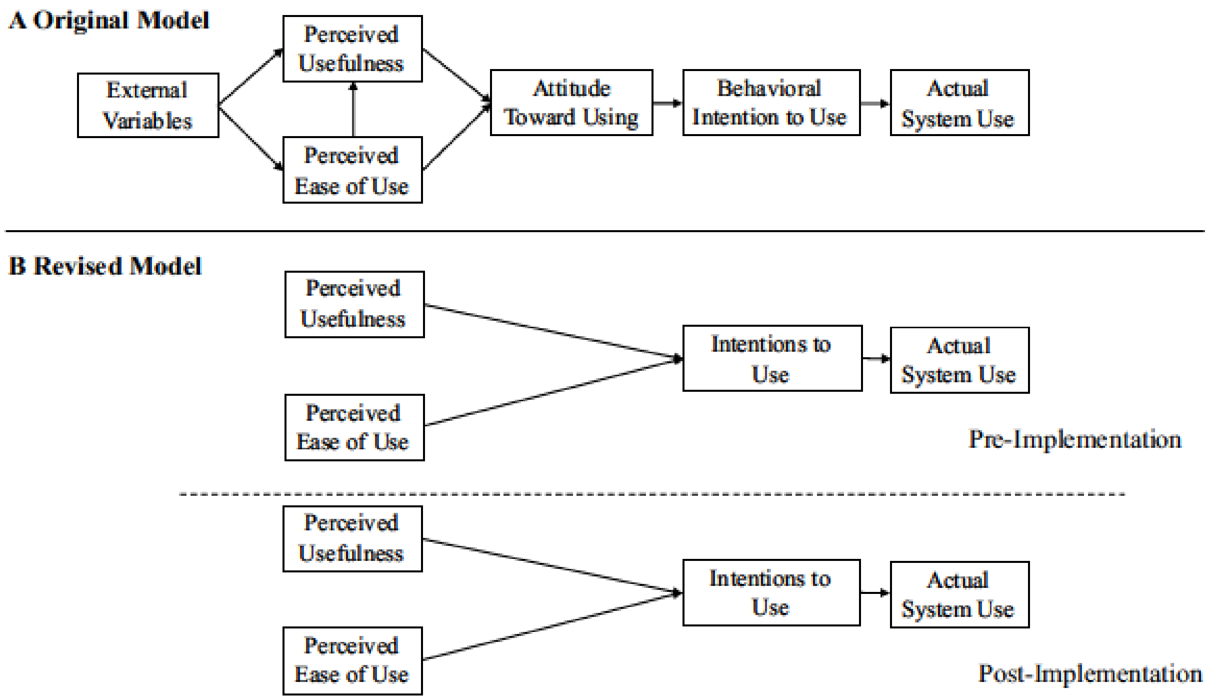


Figure 15. The Technology Acceptance Model (TAM) in (A) its original version (adapted from Davis, 1989); and (B) in its revised version (adapted from Davis et al., 1989).

In a revision of the model, Davis, Bagozzi, and Warshaw (1989) reduced the components of the model proposed by Davis (1989). Perceived usefulness and perceived ease of use were defined as beliefs, together leading to the intention to use (Figure 15B). Intention to use was assumed to lead to actual system use. However, the authors compiled a distinction between a pre-implementation version and a post-implementation version, as beliefs and attitudes are assumed to change with experience (Fazio, 1989). Within the TAM, perceived usefulness has been consistently a strong predictor of intention to use a system (Davis et al., 1989; Venkatesh & Davis, 2000). As reviewed by Marangunić and Granić (2015), the TAM has been widely used in IT research and has been shown to be a robust model to explain technology acceptance and technology usage, also on the field of smartphone usage (Joo & Sang, 2013; Park & Chen, 2007) and smartphone application usage (e.g., Lunney, Cunningham, & Eastin, 2016). The TAM has also been combined with trust based models to explain technology usage (Gefen, 2000; see Chapter 3 for details).

2.3.2 The Functional Triad. Another framework approaching the role of devices in the human-device interaction was introduced as the *Functional Triad* (Fogg, 2002). According to this model, technical devices such as computers or pocket computers (e.g., Nintendo) can function as a (1) tool; (2) a medium; or (3) a social actor (Figure 16).

The technical device as a…

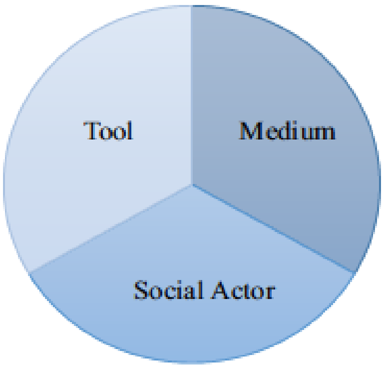


Figure 16. The functional triad postulated for a technical device, adapted from Fogg (2002).

First, technical devices become tools when they are used to gather information, for example when information is obtained from the internet. Thus, the users can increase their knowledge and their capability to complete a desired task. *Second*, technical devices can function as a medium that facilitates person's behavior, and therefore holds an enabling role. Explicitly, a device can facilitate an authentic experience (e.g., via virtual reality) or can provide a service such as data tracking (e.g., calorie tracking). *Third*, technical devices can be considered as social actors that create a relationship with the user. In this context, the device can reward a user with positive feedback and therefore shape a behavior or an attitude. For example, many games and applications contain implemented rewards such as verbal feedback, acoustic or visual cheering. Furthermore, the device can contribute to social support by connecting the user with social platforms, networks, and resources. For example, users can connect to their family and friends, professionals, or other users via social networks and platforms. From this starting point of general technology usage, researchers have approached technology usage in more specific contexts, such as health app usage.

2.4 Health App Usage

To explain health app usage, West et al. (2012) used an approach that was rooted in the *Functional Triad* framework (Fogg, 2012; see above), and the *Precede-Proceed-Model* (Green & Kreuter, 1991) that had been established to describe general health promotion planning and evaluation. The model includes predisposing factors, enabling factors, and reinforcing factors (Figure 17). According to West et al. (2012), the functional triad is comparable to the Precede-Proceed-Model, meaning that (1) tools can be translated to predisposing factors; (2) mediums are comparable to enabling factors; and (3) social actors are similar to reinforcing factors.

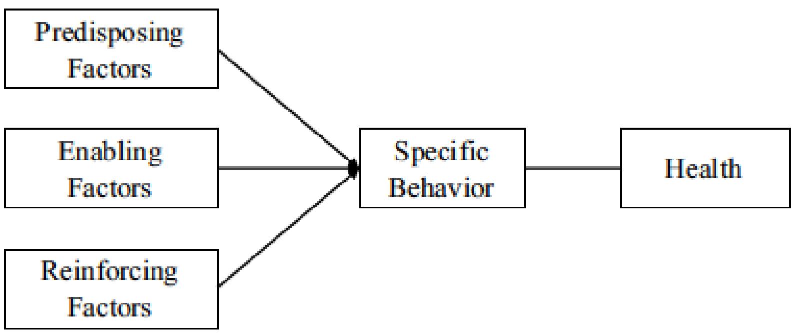


Figure 17. Visualization of the Precede-Proceed-Model, adapted from Green and Kreuter (1991).

Applied to the context of health apps, *predisposing factors* increase the user's capability and knowledge, and are antecedents of specific behavior. Health apps can enhance knowledge or awareness (e.g., by prompting nutritional values or by reminding to apply insulin etc.). Similarly, health apps can be informative with regards to specific information that is given (e.g., about symptoms of diseases). Health apps can also shape beliefs, attitudes, confidence, or motivation. With regards to *enabling factors*, health apps can provide antecedents that facilitate behavior by teaching a skill (e.g., workouts), by providing a service or selling something (e.g., the implementation of a step count), or by tracking behavior (e.g., physical activity, step count, calories). With regards to *reinforcing factors*, health apps can provide a reward or a feedback for behavior. Specifically, evaluations based on self-monitoring (e.g., reaching a certain step count) are possible. Also, interactions with other users, family, friends, and health practitioners via interfacing social networks and platforms are possible, giving the option for encouragement and trainer support. Overall, the three factors are assumed to contribute to behavior formation and enhanced health behavior.

As reviewed by West et al. (2012), most health apps include enabling factors (65.38%), for example by implementing a tracking function. Also, many apps include predisposing factors, providing health-related information (53.24%), followed by reinforcing factors (22.52%). However, the authors indicate that only 1.86% of the reviewed health apps include all three factors.

Other theories to explain behavior change in health behavior based on mobile devices have been reviewed (Riley et al., 2007). With regards to applications targeting weight loss, diet, and physical activity, one widely used theory is the Social Cognitive Theory (Bandura, 2001). The Social Cognitive Theory is a learning theory postulating that the reproduction of a behavior is shaped by three interacting determinants, including (1) personal factors; (2) behavioral factors; and (3) environmental factors. With regards to personal factors, Bandura (2001) mainly focuses a person's self-efficacy that enhances reproduction of learned behavior. The behavioral aspect refers to the response that a learner receives after a behavior (e.g., positive feedback, success). Environmental factors refer to the setting, support, and materials that are provided to conduct a behavior.

2.4.1 Fitness app usage. Although fitness app usage has been identified as a promising means to enhance physical activity and health behavior, fitness app usage has also been associated with high dropout rates. In an international comparison, 19% of Australians, 18% of Canadians, 16% of U.S., 13% of Germans, and 16% of Britons reported to have stopped tracking their health or fitness via an app, fitness band or smartwatch (GfK, 2017). As reviewed by Schoeppe et al. (2016), the participants' average usage of fitness app programs (e.g., the Australian 10,000 steps app and website) was five to six weeks, indicating a rapid decline in usage. Still, a combined usage of website and app was associated with little longer duration of usage (i.e., 8 weeks). The rapid dropout is assumed to be a consequence of lacking commitment and rather transient, irregular usage of fitness apps (Dennison, Morrison, Conway, & Yardley, 2013). However, the mean attrition rate to follow up was 17%, which is lower than the estimated attrition rate of 23 to 27% found in web-based interventions (Schoeppe et al., 2016). Thus, it has been an aim to identify predictors of the maintenance of fitness app usage on different levels using theories that have been established to predict technology or health app usage. More precisely, specific factors associated with (1) app characteristics or (2) demographical/personality factors have been identified.

First, *app characteristics* can be relevant when explaining successful and maintained fitness app usage. Using a gratification theory approach, high levels of networkability, credibility, comprehensibility, and trendiness were found to predict intention to continue using fitness apps (Lee & Cho, 2017). West et al. (2012) stress that the three factors of the Precede-Proceed-Model that have been described above (Green & Kreuter, 1991) are of high importance to facilitate behavior change: predisposing factors (e.g., knowledge about exercise), enabling factors (e.g., skills that are taught such as specific exercise routines), and reinforcing factors (e.g., rewards such as audio feedback during step count goal achievement). Schoeppe et al. (2016) reviewed that health apps are appreciated that are low in effort, pleasant to use, provide the option for self-monitoring and adequate and reliable tracking functions, have adequate privacy settings, and provide advice for behavior change including positive alerts and feedback, and are created by professionals. Furthermore, higher app usage was associated with higher perceived benefit of use (Sandholzer, Deutsch, Frese, & Winter, 2015). More generally, Yuan, Ma, Kanthawala, and Peng (2015) found that the performance expectancy associated with a fitness app is the strongest predictor of intention of continued fitness app use. In sum, both benefits (e.g., pleasant usage, rewards) and reduced risk (e.g., data security, privacy, high reliability) are of relevance for fitness app users.

Second, *socio-demographic, cognitive, and personality factors* in fitness app users have been identified as predictors of fitness app usage. Cho, Park, and Lee (2014) found health consciousness directly associated with the extent of health-app use. Health information orientation and eHealth literacy were also associated with the extent of health-app use, being mediated via health-app use efficacy. Dennison, Morrison, Conway, and Yardley (2013) found that if the users had low trust in the functionality of a fitness app, they would be likely to cease from using it. Furthermore, higher app usage was associated with younger age and being female, and a personal interest in and positive attitude towards smartphone apps (Sandholzer et al., 2015). In the field of research on motivational aspects, fitness app usage has been connected with perceptions of accomplishment and goal attainment (i.e., autonomy and competence needs) and personal long-term goals (Clinger, 2015; Rönkkö, 2018). With regards to personality related variables, little evidence for the existence of substantial connections to fitness app usage has been provided yet. Looking at the Big Five personality variables of extraversion, conscientiousness, openness, agreeableness, and neuroticism (Costa

& McCrae, 1992), high levels of neuroticism were found to predict calorie tracking in fitness app users (Embacher, McGloin, & Atkin, 2018).

In sum, a range of both app and user related aspects have been identified that can contribute to dropout from or longer duration of fitness app usage. Besides personal and demographic factors that indicate the importance of experience and familiarity of new technologies, perceived usefulness and also potential risks associated with fitness apps appear to be of relevance in maintenance of fitness app usage.

Overall, this Chapter 2 provided insight into the field of digitalization and outlined how digitalization has been applied to the health context. Specifically, it was delineated how fitness apps can contribute to enhance physical activity. To explain the adoption and maintenance of technology, various approaches ranging from general technology to specific fitness app usage were presented. Beyond the background of the diverse risks that were associated with technology usage in general and with fitness app usage in a specific way, trust emerges as an important aspect to consider when understanding fitness app usage.

3. Trust

Facing potential risks in relations of any kind, trust has been identified as a powerful and important concept to explain why people form relationships, collaborate with each other, or use technology (Mayer et al., 1995; McKnight et al., 2011; Rousseau, Sitkin, Burt, & Camerer, 1998). The following chapter will therefore point out the role of trust, its definitions and applications. First, the concept of trust, including diverse approaches to explain trust is targeted. Following the nomological network of trust theory, forms of trust, objects of trust, trustworthiness, the trustor, and the act of trust are presented. In a next step, the association between trust and digitalization is depicted, followed by models describing trust in the context of technologies and specific technology usage. Additionally, trust related concepts such as control, risk, and benefit are presented, including its applications to technology usage. Overall, Chapter 3 sheds light onto the fields of risk and benefit (i.e., trust), their application to communication technology, and their overlap, representing trust in technology (Figure 18).

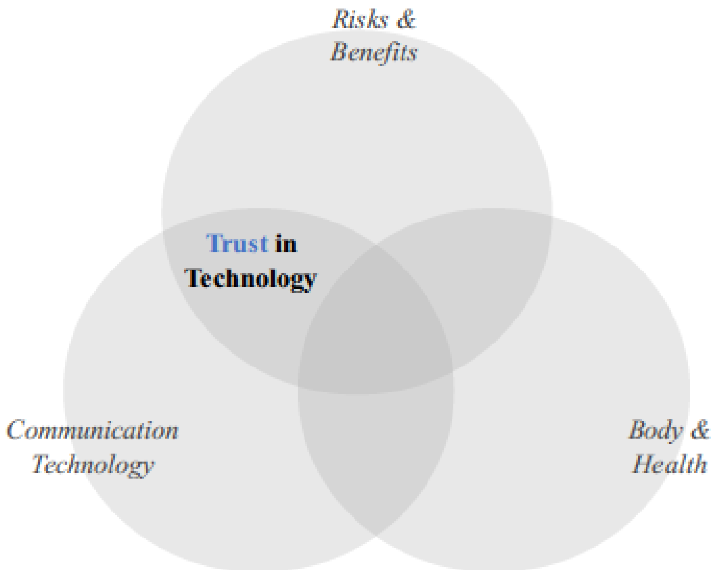


Figure 18. Visualization of trust in technology as an intersection of digitalization and the integration of risks and benefits targeted in this chapter.

3.1 Trust Concepts

In scientific research, trust has been subject to examination in several disciplines, principally in psychology, sociology, and management. In its inherent sense, the concept of trust has been approached differently, explicitly speaking as a psychological state or as an interpersonal relation, depending on the scientific discipline.

From *psychology perspective*, trust is regarded as a state that lies within a person. It has been described as a mental state or attitude (Castelfranchi & Falcone, 2010), or as a state of willingness to make oneself vulnerable under risky conditions (Mayer et al., 1995; Schoorman, Wood, & Breuer, 2015). In addition, it is often stressed that the willingness to be vulnerable is based on positive expectations of the intentions or behaviors of another (McEvily & Tortoriello, 2011; Rousseau et al., 1998).

From *sociology perspective*, trust has been described as a relation between the trustor and the trustee (the object of trust), laying the focus on the social significance of trust. Instead of a property within a person, trust is viewed as a "quality of relationship" and a property of collective units (Sztompka, 1999; p. 60) Trust is also conceptualized as a mechanism serving to reduce complexity (Luhmann, 1968). This viewpoint has been established beyond the background of the rising complexity that is increasingly prevalent in modern societies. Therefore, trust has the function for the individual to still be able to act in a complex environment that goes beyond the limited knowledge of a person (Luhmann, 2001).

Overall, trust is viewed as relational construct, that is an element of a relationship between two units: the trustor, who trusts the other unit (the object of trust), and the trustee receiving trust (Schoorman et al., 2015). Furthermore, scholars across the disciplines agree that trust is based on perceptions and experiences in the past, and oriented toward the future. According to them, trust is easier to destroy than to build, refers to a situation, object, performance, or problem, and it is based on a free decision (Blöbaum, 2016; Lewicki et al., 2006; Mayer et al., 1995). Furthermore, trust entails a risk that is higher than a benefit and also lies within an act of trust. In this act of trust, the trustor makes himself or herself vulnerable to the other unit.

3.1.1 Trust as a belief, attitude, intention, or behavior. As psychological and sociological perspectives on trust are diverse, so is trust varyingly considered as a belief, an attitude, an intention, or a behavior. Apart from trust research, Ajzen and Fishbein (1980) provided a framework that helps to differentiate and to integrate these concepts, i.e., the Theory of Reasoned Action (TRA; Figure 19). First, general beliefs and perceptions lead to more specific attitudes towards something or someone. Second, specific intention formation is regarded as a function of several attitudes, leading to a concrete behavior. Thus, the process of intention and behavior formation can be described by a chronological sequence. Within this sequence, the content's specificity increases from general and unspecific beliefs to concrete behavior. Applied to the trust concept, trusting beliefs are rather unspecific, whereas trusting behavior is more situation specific.

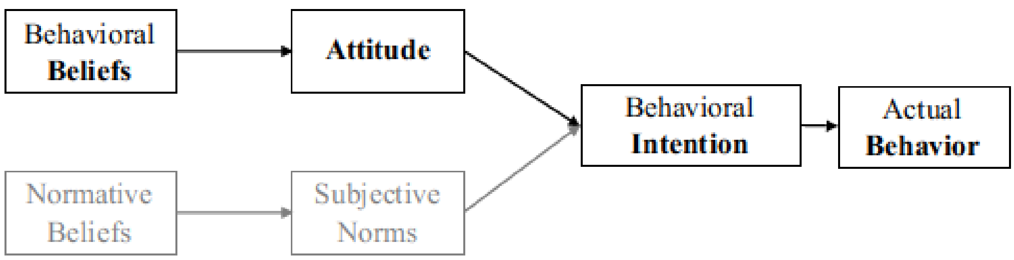


Figure 19. Visualization of the Theory of Reasoned Action (TRA), adapted from Ajzen and Fishbein (1980).

Scholars introducing models to understand the process of trusting varied in how they integrated beliefs, attitudes, intentions, and behavior to define trust. Sometimes, one single aspect of behavior formation was used to define trust. For example, Rotter (1971) focused solely on the aspect of attitudes when describing trust. In contrast, other scholars used a variety or all aspects to describe the process of trust. For example, Lee and See (2004) integrated trusting beliefs, trusting attitudes, trusting intentions, and trusting behavior in their approach. Also, scholars varied in how clearly the aspects of intention formation were labelled. For example, some scholars explicitly named the aspects of behavior formation (e.g., "beliefs" in Lee & See, 2004; McKnight et al., 1998), whereas others referred to unspecific "trust" (e.g., Rempel, Holmes, & Zanna, 1985). The differentiation in these stages makes trust a construct varying in specificity and the degree of how concrete to a specific action it is regarded.

Trusting beliefs are the root of the trust process and function as a basis of information, leading to attitude formation (Ajzen & Fishbein, 1980). In trust research, McKnight et al. (2011) introduced their model as a model of trusting beliefs, leading to concrete intentions and behavior as outcome variables. In an integrative model of trust, Mayer et al. (1995) introduced aspects of perceived trustworthiness as trusting beliefs, leading to a trusting intention and the act of trusting.

Trusting attitudes are based on beliefs and represent an expectation about the likelihood that an event occurs. Rotter (1971) defined trust as an expectancy that the communication of someone can be relied on. Rempel et al. (1985, p. 96) regarded trust as an "expectancy related to the subjective probability an individual assigns to the occurrence of some set of future events". Therefore, trust has been conceptualized as an expectation that an advantageous event occurs.

Trusting intentions are a willingness to act in a certain way. This perspective includes the intention to engage in a behavior or to make oneself vulnerable. Mayer et al. (1995) defined trust as a willingness to make oneself vulnerable. Also, trust was defined as the willingness to rely on an exchange partner (Moorman, Deshpande, & Zaltman, 1993) or as a "willingness to place oneself in a relationship that establishes or increases vulnerability with the reliance upon someone or something to perform as expected" (Johns, 1996, p. 81).

Trusting behavior is the concrete outcome that is based on intention formation. Sometimes, trust has been defined as the state of risk or vulnerability in terms of a behavioral result (e.g., Deutsch, 1960). Kramer (1999, p. 571) also defined trust as a "state of perceived vulnerability or risk".

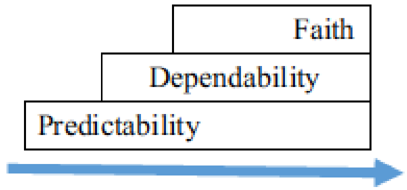
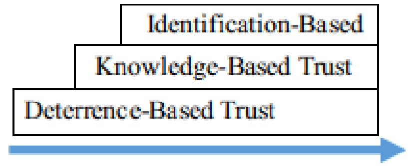
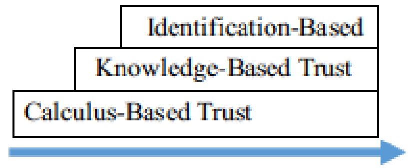
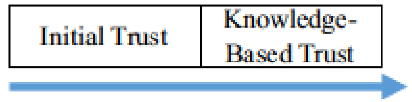
3.2 Forms of Trust

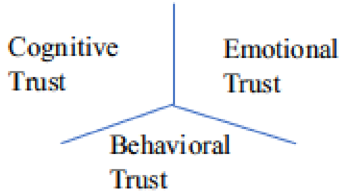
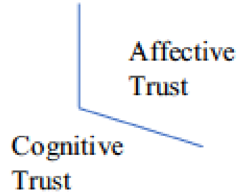
Across scholars, disciplines, and contexts, trust has often been described as a multidimensional model. However, a high variety exists in assumptions about potential successions and other forms of trust that are presented in detail below (see Table 3 for an overview). In general, trust has been described (1) as a *sequential concept* including stages of trust that develop throughout a process (e.g., predictability, dependability, and faith); (2) as *distinct forms of trust* where one form of trust is prevalent, whereas the other is not (e.g., swift trust and slow trust); (3) as *parallel forms of trust* that co-exist on different dimensions (e.g., cognitive trust and affective trust).

3.2.1 Sequential concept. Some scholars understand trust as a sequential concept that changes throughout the relationship between the trustor and the trustee. In sequential models of trust, it is considered that the quality and quantity of knowledge including personal experience change during a relationship. As knowledge and experience shape trust, it has also been assumed that the quality of trust changes over time. In general, trust is considered to be more stable and robust when trust is based on (1) much experience in contrast to little experience; and (2) several factors compared to single factors, (McKnight, Cummings, & Chervany, 1998). In the following, sequential models of trust are presented. These models are mainly focusing on trust from a sociological perspective (Lewicki & Bunker, 1996; Rempel et al., 1985).

Table 3

Forms of Trust

Trust Concept	Basis of Trust	Integration in Mayer et al. (1995)	Tested on the field of	Illustration of the Model
<u>1. Sequential Concept</u>				
Rempel (1985)	Predictability Dependability Faith	Ability Integrity Benevolence	Interpersonal Trust	
Shapiro et al. (1992)	Deterrence-based trust Knowledge-based trust Identification-based trust	Ability Integrity Benevolence	Trust in Business Relationships	
Lewicki & Bunker (1996)	Calculus-based trust Knowledge-based trust Identification-based trust	Ability Integrity Benevolence	Trust in Organizational Relationships	
McKnight et al. (1998)	Initial Trust Knowledge-Based Trust		Trust in Organizational Relationships	

<u>2. Distinct Forms of Trust</u>				
Meyerson et al. (1996)	Slow Trust Swift Trust		Trust in Temporary Groups	Slow Trust | Swift Trust
Wei & Yucetepe (2013)	Competence Trust Goodwill Trust	Ability, Integrity Benevolence	Interpersonal Trust	Competence Trust | Goodwill Trust
<u>3. Parallel Forms of Trust</u>				
Lewis & Weigert (1985)	Cognitive Trust Emotional Trust Behavioral Trust	Ability, Integrity Benevolence	Interpersonal Trust	
McAllister (1995)	Cognitive Trust Affective Trust	Ability, Integrity Benevolence	Interpersonal Trust in Organizations	

3.2.1.1 Predictability, dependability, and faith. Trust has been regarded as a dynamic attitude that changes throughout the relationship with the trustor. Rempel et al. (1985) differentiated between *predictability, dependability,* and *faith* that evolve at different stages and in a fixed order. Each stage is building up on previous stages. At early stages of trust, *predictability* is dominant. Predictability refers to stable and predictable actions that can be observed in a person and that are comparable to the evaluation of the trustee's ability. At a later stage, *dependability* evolves. When a trustor has experienced a range of situations that also involve risks and vulnerability, the experiences can be accumulated to an evaluation of a more stable disposition in the trustee. This assessment is defined as dependability and is congruent with a person's evaluation of integrity. Going beyond dependability, *faith* is a more generalized belief that evolves on the basis of past experience. Faith refers to the belief that a person will act as he or she has acted in the past. Also, faith has a stronger emotional connotation than predictability and dependability. Faith is comparable to the perceived benevolence of a person.

3.2.1.2 Calculus-based, knowledge-based, and identification-based trust. Another prominent sequential model of trust has been established on the field of trust in business relationships (Shapiro, Sheppard, & Cheraskin, 1992). In business relations, especially the development of trust is of interest as people constantly form new working groups and need to rely on co-workers after short time. Therefore, the models presented below (e.g., Lewicki & Bunker, 1996, Shapiro et al., 1992) describe and explain relationships when two parties are entering into a new relationship. Shapiro et al. (1992) initially introduced the stages *deterrence-based trust*, *knowledge-based trust*, and *identification-based* trust. *Deterrence-based trust* refers to the consistency and contingence of a person's verbal communication and behavior. For example, high deterrence-based trust describes that a person who threats a punishment will execute the punishment afterwards. *Knowledge-based trust* refers to a person's behavioral predictability and the reliance on past experience. Therefore, it is necessary to collect an amount of information about a person's behavior in the past that is based on regular communication. Consequently, knowledge-based trust can evolve after a sufficient time of experience across situations. *Identification-based trust* goes beyond knowledge about a person's behavior and refers to empathy towards a trustee. Also, identification-based trust is characterized by an emotional connection and shared values between a trustor and a trustee. Identification-based trust reflects the identification with the other party's desires and intentions as well as mutual understanding.

The model introduced by Shapiro et al. (1992) was adapted and modified by Lewicki and Bunker (1996), also in the field of professional work relationships. Lewicki and Bunker adapted the stages of knowledge-based trust and identification-based trust but changed deterrence-based trust into *calculus-based trust*. The authors argued that deterrence-based trust has a strong connection with threatening behavior and the expectation of punishment. In contrast, calculus-based trust is a more neutral and also broader description of the behavioral control. Calculus-based trust refers to the tradeoff between costs and benefits and the related (expected positive and negative) consequences. Lewicki and Bunker (1996) highlight that trust evolves and changes gradually from calculus-based trust to knowledge-based trust, and finally to identification-based trust. However, not all stages develop fully in trusting relationships. Sometimes, trust can stay on the first or second stage. For example, an employee who does not share his unsympathetic boss's values would hardly develop identification-based trust, even after years of close collaboration.

Shapiro et al.'s (1992) and Lewicki and Bunker's (1996) models that had been established on the field of business relationships, were also adapted to interpersonal relationships. In this context, McAllister, Lewicki, and Chaturvedi (2006) argued that emotional processes are more dominant in general interpersonal relationships compared to organizational relationships. Thus, the component of *affective trust* was added to knowledge-based trust and identification-based trust. Affective trust is introduced below in the section targeting other forms of trust.

3.2.1.3 Initial trust and knowledge-based trust. Based on the trust concept introduced by Lewicki and Bunker, McKnight et al. (1998) defined two sequential forms of trust in the context of research on trust in organizations. Explicitly, McKnight et al. (1998) differentiated between early *initial trust* and late *knowledge-based trust*. These two forms are described in detail in the section introducing McKnight et al.'s (2011) model of trust in a specific technology.

3.2.2 Distinct forms of trust. Besides sequential models of trust, other scholars have approached trust from a perspective that assumes that there are distinctive different types of trust. One distinct conceptualization is based on Meyerson, Weick, and Kramer (1996). In the context of organizational relationships, the authors differentiated between *swift trust* and *slow trust*. These two forms of trust vary in the speed they are developing. *Swift trust* evolves in new established groups and is characterized by a rapid formation of trust. In contrast, *slow trust* can be observed in routine and profound relationships and changes slowly.

Another more recent distinction of trust was proposed by Wei and Yucetepe (2013). The authors differentiate between *goodwill trust* and *competence trust. Goodwill trust* refers to a trustee's morality and willingness to do good for the trustor. Therefore, goodwill trust is comparable to Mayer et al.'s (1995) concept of benevolence, Lewis and Weigert's (1985) affective trust, or Rempel's (1985) faith. Competence trust relates to a trustor's expertise on a field, enabling him or her to successfully perform a given task. Therefore, this concept is similar to Mayer et al.'s (1995) concept of ability, Lewis and Weigert's (1985) cognitive trust, or Rempel's (1985) predictability.

3.2.3 Parallel forms of trust. Also, trust can be regarded as a construct that manifests on different co-existing dimensions, for example on affective and cognitive dimensions. In the models described below, no assumptions about potential sequentiality among these dimensions are made.

Grounded in research on organizational relationships, McAllister (1995) differentiated between *affect-based trust* and *cognition-based trust.* Affect-based trust describes emotional aspects such as mutual interest, care and concern between workers. Cognition-based trust rather focuses on the perception of the co-worker's competence and reliability.

Similarly, trust has been described as a social reality between persons that manifests on *cognitive, emotional*, and *behavioral* dimensions (Lewis & Weigert, 1985). The cognitive dimension describes aspects of rational considerations that are present in trust relationships. The emotional dimension describes the emotional bond between persons (e.g., friendship) that influences the evolution of trust in relationships. The behavioral dimension of trust describes the observable actions between persons that can also influence the cognitive and affective dimensions (e.g., an action provides information for a cognitive-based decision).

3.2.4 Trust and distrust. Across scholars, trust and distrust have been regarded as related, but divergent constructs (Guo, Lumineau, & Lewicki, 2017). However, diverse perspectives exist about how trust and distrust are related to each other. Reviewing the literature, Guo et al. (2017) outlined three models of how the interrelations of trust and distrust are outlined across scholars (Figure 20).

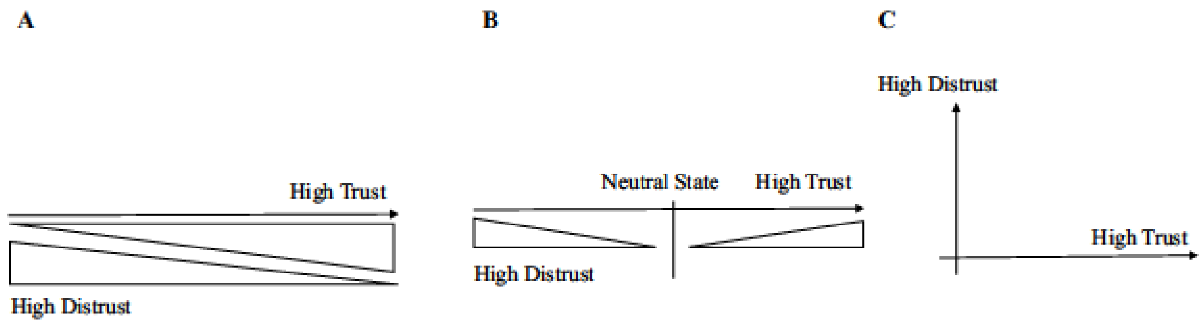


Figure 20. Visualization of models specifying the relations between trust and distrust. *Note:* (A) Trust and distrust as two endpoints of one dimension; (B) Trust and distrust with a neutral state in between; (C) Trust and distrust as two distinct dimensions; adapted from Guo et al. (2017).

Especially during early trust research, it was assumed that trust and distrust are two endpoints of a one-dimensional relationship (Figure 20A). This dimension ranges from trust on the one endpoint to distrust on the other endpoint (Lewis & Weigert, 1985; Rotter, 1971). Explicitly, distrust was assumed to be the polar opposite of trust. Therefore, low trust expectations were regarded as indicators for distrust, and vice versa.

Later, scholars argued that violated trust is not exactly the same as distrust (Zucker, 1986). It was differentiated between trust and distrust, and an additional neutral state in between (Figure 20B). Consequently, distrust does not incorporate the absence of trust. Distrust involves the expectation that the distrusted party behaves in a way risking the trustor's security and well-being (Ullmann-Margalit, 2004).

Other scholars argue that trust and distrust are two distinct constructs that need to be regarded on two different dimensions (Lewicki, McAllister, & Bies, 1998; Lewicki et al., 2006; Lumineau, Eckerd, & Handley, 2015). The dimensions of risk and trust are regarded as linked, but also as dimensions that can each vary on their individual degree (Figure 20C). Thus, high or low levels of trust and high or low levels of distrust can co-exist at the same time. For example, negotiation often includes trust on certain dimensions that had been established in relations and that might also be built during the progress of negotiation. Also, negotiation can simultaneously create elements of distrust on other dimensions during the progress (Lumineau et al., 2015).

3.3 Objects of Trust

Still, when referring to trust, it is important to distinguish between trust, its antecedents, outcomes, and the related objects of trust (Mayer et al., 1995). Going beyond the sociological perspective of trust as a mechanism on society level, the object of trust can be regarded in a more elaborate fashion from psychological perspective. Whereas some scholars claim that a trustee can only be a person (Friedman, Khan, & Howe, 2000; Mayer et al., 1995), other scholars (e.g., McKnight et al., 2011) argue that the trusted object can even be a technology itself. To classify objects of trust, Blöbaum (2016) distinguishes between trust in (1) people as role holders (e.g., teachers, medical doctors); (2) trust in institutions or organizations (e.g., companies, schools); and (3) trust in social systems (e.g., the media, politics, health care). Whereas the system is regarded as a stable existence, institutions and role holders are subject to change (i.e., digitalization). Change and familiarity are of special relevance in trust formation and perpetuation. If a trustor has gained experience with institutions or role holders, familiarity emerges. The experience of familiarity is also referring to expectations about the future, i.e., that everything is functioning as usual. Therefore, high familiarity implies a lack of uncertainty and risk. In an extreme form of familiarity, trusting even becomes obsolete. However, when environments and situations change (e.g., in the context of the shift from analogous processes to digitalized processes), the state of familiarity disappears, and trust needs to be rebuilt. From the starting point of different objects of trust described above, four forms of trusting relationships emerge (Figure 21).

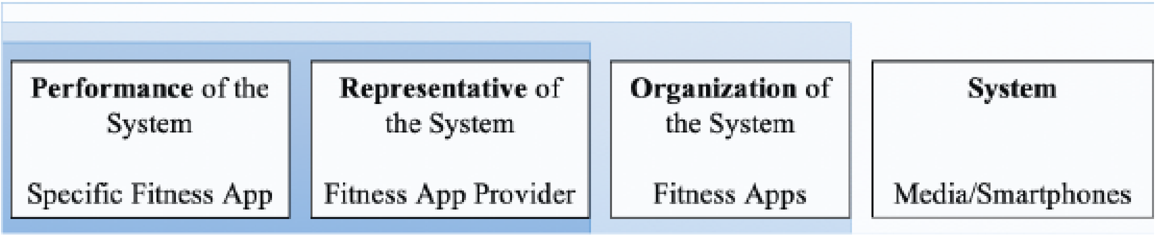


Figure 21. Four forms of trusting relationships, adapted from Blöbaum (2016).

The model illustrates the different points of reference within the trusted object. Using the example of a fitness app, the following relationships evolve: A relationship with (1) the performance of the system (e.g., a fitness app on the smartphone); (2) a representative of the system (e.g., a staff member of the app provider company handling the data and codes); (3) organizations of the system (e.g., the app provider company); (4) the system itself (the media or health care system). The elements of the model are conceptualized in a contingent relation, varying in their abstraction level (i.e., a staff from an app provider company is associated with the company which in turn is part of the media system).

The trust concept has been traditionally defined as interpersonal trust describing a relationship between a trustor and a trustee (e.g., Mayer et al., 1995; Rousseau et al., 1998). However, the trust concept has also been extended and successfully applied to human-technology interaction context (McKnight et al, 2011). As described above, an object of trust can represent various aspects related to human beings, technologies, or abstract systems. Recently, it has also been indicated that the own body can be an object of trust (e.g., Mehling et al., 2012; Sharon & Zandbergen, 2017). Although rooted in research on body awareness, it can still be assumed that body trusting corresponds with aspects of traditional trust definitions. In general, decisions and dependence under risky conditions have been linked to the trust concept (Lewicki & Bunker, 1996; Mayer et al., 1995; McKnight & Chervany, 2006). So, first, a person must perceive some kind of body sensation in a certain intensity (e.g., itchiness, soreness of a joint, nausea, pain in the chest, but also hunger, heat, or fatigue).

Depending on whether a person trusts or does not trust their body sensations, he or she might find different ways to decide about their health behavior: Does he or she continue exercising, does he or she perform a specific exercise move, does he or she stop or continue to eat, or does he or she attend a medical doctor? All these decisions can have important implications for a person's health and therefore underlie risky conditions. Hence, implications of body trusting in a general health and also in an exercise specific way can theoretically be connected to traditional trust theories. However, the conceptualization of body trusting as an aspect of trust in its traditional designation has yet to be examined. Thus, studies are needed to connect body trusting with other trust related variables that are applied in a similar context (e.g., trust in technology to understand fitness app usage). These questions can be answered by conducting empirical studies, and by comparing the measurement tool with traditional trust theories. The development of such a theoretical concept is outlined in detail in Chapter 4.

3.4 Trustworthiness

Trustworthiness is the evaluation and attribution of characteristics referring to the trusted object, and evolves in the trustor. In the literature, a broad range of attributes that can be assigned to the trusted object have been described and discussed as perceived trustworthiness. These attributes were identified and reviewed by Mayer et al. (1995), for example including availability, loyalty, expertness, expertise, benevolence, and openness. Providing a systematic aggregation of these attributes, three core factors were identified that are described below: *ability*, *benevolence*, and *integrity*. Trustworthiness and each of its factors are assumed to vary on a continuum, ranging from low trustworthiness to high trustworthiness. Trustworthiness—i.e., ability, benevolence, and integrity—was found to predict an individual's intention to trust (Gill, Boies, Finegan, & McNally, 2005), and to increase with experience over time (Alarcon, Lyons, & Christensen, 2016): As new information, such as prior behavior, becomes available, the trustor uses this information to reevaluate the perceived trustworthiness of the trustee. Thus, propensity to trust was found to predict subsequent trusting behaviors in computer-mediated dyadic research on trust using a longitudinal design (Alarcon et al., 2018). In the following, the three sets of trustworthiness identified by Mayer et al. (1995) are described.

3.4.1 Ability. Ability refers to a set of competencies and characteristics that are assigned to the trustee. Across scholars, ability has been regarded as a central element of trust (Cook & Wall, 1980; Jones, James, & Bruni, 1975), and has also been described as competence (Butler, 1991) or expertise (Giffin, 1967) of a trustee. Abilities are specific to the domain of relevance, for example to fulfill a specific task. Given that high ability beliefs are present, it is anticipated that the relevant task reaches a certain degree of quality. For example, a medical intervention is assumed to be a successful treatment of a disease. Ability is regarded to be domain specific. For example, a person with high competencies in the field of relevance (e.g., a medical doctor) would be regarded as capable to cure a disease, whereas a person with high competencies in another field (e.g., a photographer) would not. Similarly, the medical doctors' abilities in cooking or his knowledge in Greek history would be of low relevance during the evaluation of a medical intervention.

3.4.2 Benevolence. Benevolence describes the trustee's intention to act in the trustor's interests. A trustee who is assigned to be benevolent has good intentions to do good for the trustor. Therefore, benevolence implies the presence of an emotional attachment between the trustee and the trustor, which is complemented by low egocentric interests in profit (Mayer et al., 1995). Aspects of trustworthiness that are similar to benevolence have been described as (low) motivation to lie (Hovland, Janis, & Kelley, 1953) or loyalty (Butler & Cantrell, 1984).

3.4.3 Integrity. The perceived integrity refers to the credibility and consistency of a trustee. Therefore, the evaluation of integrity is influenced by the reliability of the trustee's past actions. Integrity manifests in the belief that the trustee has a strong sense of justice, adheres to credible communications, and acts in congruence with his or her words (Mayer et al., 1995). Overall, integrity means that the trustee adheres to principles that are considered as adequate by the trustor. Integrity was described as an aspect of trustworthiness by Lieberman (1981). Similarly, integrity was described as the character of a person (Gabarro, 1978), and more specifically as a person's fairness (Hart, Capps, Cangemi, & Caillouet, 1986).

Together, the three aspects of ability, benevolence, and integrity form the perceived trustworthiness. Each of these aspects can vary independently of the others, however this does not imply that the characteristics of the trustee are unrelated. The aspects of trustworthiness describe *subjective* perceptions of the trustor with regards to the trustee's characteristics and do not represent objective features.

3.4.4 An Integrative Model of Trust. The three aspects of trustworthiness described above form core components of a model of trust that was proposed by Mayer et al. (1995) based on a comprehensive literature review. Overall, the model integrates components of trust, its antecedents (i.e., trustworthiness and the trustor's propensity) and outcomes (Figure 22).

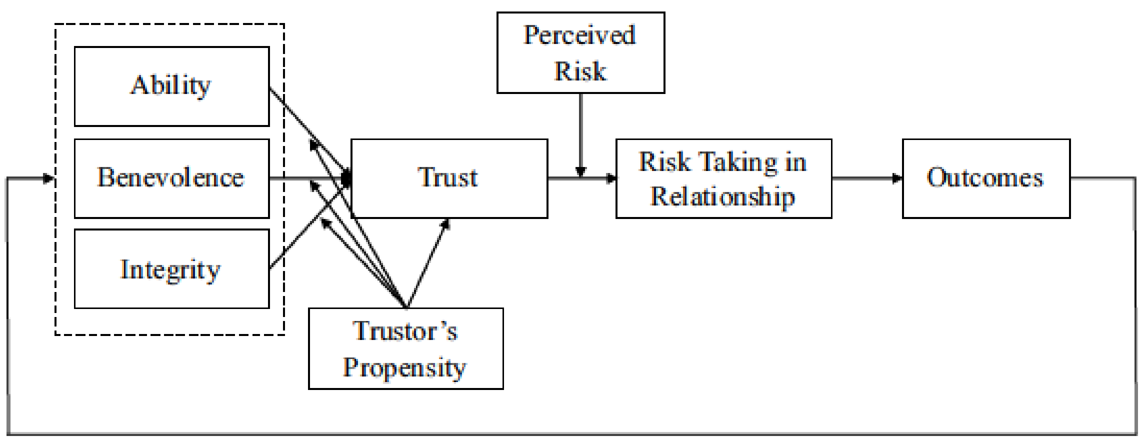


Figure 22. The Integrative Model of Trust, adapted from Mayer et al. (1995).

To date, their model is the most accepted and the most widely used framework model in trust research, as reviewed by Lee and See (2004), and by Rousseau et al. (1998). Combined with the individual trust propensity, the trustor's assessment of the trustee's trustworthiness leads to trusting that is regarded as an intention to make oneself vulnerable. In interaction with the perceived risk associated with the act of trust, people engage in potentially risky behaviors by interacting with the trustee (Mayer et al., 1995). The information provided via the outcomes delivers information that can be used to reassess the perceived trustworthiness, i.e., ability, benevolence, and integrity.

The integrative model of trust was established to explain trust based on propensity to trust and the trustor's perception of trustworthiness, even during early stages of relationship between two parties. However, at different stages of interactions—or even before—aspects of trustworthiness can be of different relevance and availability. For example, Mayer et al. (1995) stated that an experienced trustor can be able to gain integrity- and benevolence-related information based on personal experience. In case of lacking experience with the trustee, ability-related information can be obtained by third person's evaluations. However, little information referring to the trustee's benevolence might be available at early stages of trust as benevolence includes aspects that relate to first-hand experience and interaction. Furthermore, it has been indicated that propensity to trust can only predict trustworthiness in unfamiliar settings when initial trust is present (Alarcon et al., 2016). With growing experience, propensity to trust decreases in relevance, and the perceived trustworthiness increases in relevance (Alarcon et al., 2016, 2018; Gill et al., 2005).

The model proposed by Mayer et al. (1995) has been widely adapted by researchers across diverse disciplines to explain behavior based on a trustee's perceived trustworthiness. For example, the integrated model of trust was adapted to marketing relationships, communication in organizational teams, or laypeople's trust in experts (Alhazmi, 2019;

Breuer, Hüffmeier, Hibben, & Hertel, 2019; Hendriks, Kienhues, & Bromme, 2015). In the field of sport and exercise sciences, the model has been successfully applied to explain behavior in sport organizations, doping, and coach-athlete relations (Dreiskämper, 2014; Dreiskämper, Pöppel, & Strauss, 2016; Querfurth-Böhnlein, 2018).

3.5 The Trustor

In trusting relations, several attributes and circumstances that are associated with the trustor are of relevance. Specifically, knowledge and experience referring to a trusted object shape the trustor's evaluation. Furthermore, personal features and also situational features are of relevance that are described below.

3.5.1 Knowledge and experience. First, knowledge and experience are central aspects that influence the trustor's perception and evaluation. Knowledge about the trusted object refers to specific and situation-relevant aspects that are associated with the object of trust. For example, a person has large knowledge about a company selling health insurance, because he or she previously did an elaborate research on the internet. Consequently, he or she would lay greater trust in this organization and would buy an insurance from this company rather than from an unknown company. Knowledge about a trustee has been connected with trust in previous research (Ashley, Poepsel, & Willis, 2010).

Besides knowledge, experience shapes the evaluation of trustworthiness: Experience is based on previous interactions that can even go back to early childhood experience (Sztompka, 1999). Experience can be based on direct experience (first-hand experience) or can refer to experience of others (second-hand experience). In general, longer duration of positive experience is assumed to enhance the perception of trustworthiness of a trusted object (Mayer et al., 1995).

3.5.2 The trustor's personal features. Another aspect within the trustor are the trustor's personal features. Personal features are unspecific to situations and lead to a trusting act in interaction with situational features. Blöbaum (2016) distinguishes between three factors that lie within a person (Figure 23): (1) *sociodemographic features* (i.e., age, gender, education level); (2) *general trust propensity*; and (3) *general risk propensity*.

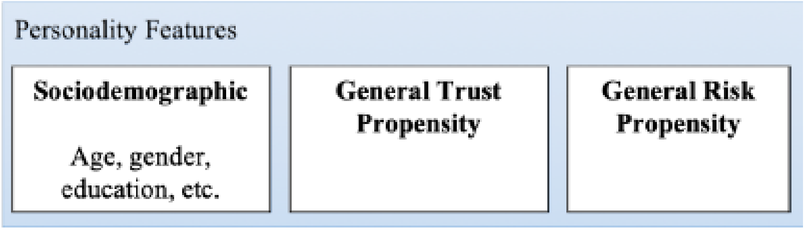


Figure 23. Personality features in the trustor: Sociodemographic features, general trust propensity, and general risk propensity, adapted from Blöbaum (2016).

In trust research, *sociodemographic features* have been examined in the context of trust in media. While gender was not found to be associated with trust in media, higher levels of education were associated with lower levels of trust in the media, and higher age was associated with higher levels of trust in traditional media compared to digital media (Tsfati & Ariely, 2014).

General trust propensity is regarded as a within-person attribute that refers to a person's general ability to trust (Gill et al., 2005; Mayer et al., 1995), and that has been found to be stable across situations and time (e.g., Alarcon et al., 2016, 2018). General trust propensity is assumed to influence both trust and its antecedents (Mayer et al., 1995). The propensity to trust is particularly of relevance when a new relationship begins and the trustor has no knowledge about and no former experience with the trustee (Colquitt, Scott, & LePine, 2007; Mayer et al., 1995; McKnight & Chervany, 2001). The propensity to trust has been identified as a predictor of perceived ability, benevolence, and integrity, however only in individuals who have had little direct experience with the trustee (Murphy, 2003). Similarly, propensity to trust was only related to trusting intentions when the information to evaluate the trustworthiness was ambiguous (Gill et al., 2005). If the information to evaluate trustworthiness was unambiguous, propensity to trust was not related to trusting intentions in this study. Colquitt et al. (2007) conducted a meta-analytic structural equation modeling and found that trustworthiness partially mediates the influence of propensity to trust whereas propensity to trust explained incremental variance in trust. Using a longitudinal design, it was found that the propensity to trust can influence initial perception of trustworthiness, but cannot predict the change in trustworthiness over time (Alarcon et al., 2016). Van der Werff and Buckley (2017) found that propensity to trust affects the intention to rely and to disclose information. Differentiating between levels of familiarity, propensity to trust led to perceived trustworthiness in the group faced with unfamiliar information compared to the group faced with familiar information (Alarcon et al., 2016). Similarly, it has been indicated that the influence of trust propensity on trust decreases over time (Levin, Whitener, & Cross, 2006). In computer-mediated dyadic research on trust, propensity to trust was found to predict the perceived trustworthiness, but not the participants' trust behavior over time (Alarcon et al., 2018).

General risk propensity is a construct that is similar to general trust propensity and it is referring to the individual propensity to engage in risky behavior. Therefore, high levels of risk propensity are assumed to lead to an act of trust, despite of low perceived trustworthiness. General risk propensity has scarcely been targeted in scientific research yet (Mayer et al., 1995).

3.5.3 Situational features. Situational features are specific aspects in a trustor's environment that influence the act of trust. Depending on how a concrete situation is perceived, a person would decide to trust or not to trust (McKnight et al., 1998). According to Blöbaum (2016), situational features affecting the act of trust can be classified into (1) *context*; (2) *relevance*; (3) *specific perception of risk*; and (4) *communication situation* (Figure 24).

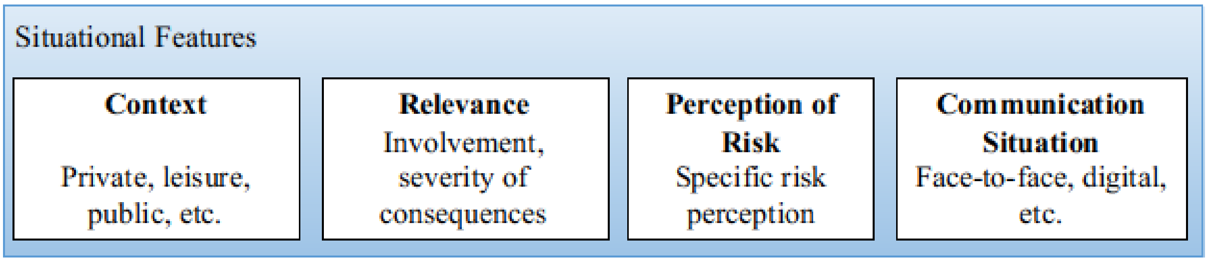


Figure 24. Situational features in the trustor: context, relevance, specific perception of risk, and communication situation, adapted from Blöbaum (2016).

First, depending on the *context* (e.g., work, leisure), behavior is interpreted differently. Therefore, different contexts lead to different evaluations of the trustor and the establishment of trust. For example, digital documentation of work could contribute to transparency in the work context. In contrast, digital documentation in private context could be interpreted as surveillance.

Second, the *relevance* of a situation influences the importance of aspects of trustworthiness. The relevance is connected with the personal importance and engagement in a situation. For example, a person who is threatened by an approaching hurricane would perceive the trustworthiness of a weather report provider more significant than a person who is interested in whether to wear the pullover for a walk or not.

Third, the *perception of risk* lies within the trustor. Also, the consequences and actual risks associated with the act of trust have a direct implication on the trustor. The perception of risk is a subjective evaluation made by the trustor and can influence all antecedents of trusts. The aspect of risk will be targeted in detail below.

Fourth, the *communication situation* can include different numbers of persons who are involved in a situation (e.g., one-to-one vs. groups). Also, the situation can entail different settings (e.g., face-to-face vs. via the media). The communication situation can influence the assessment of trustworthiness. For example, in face-to-face interactions, the situation provides cues to evaluate the trustworthiness of a person that are different to cues that are provided in a digital setting (i.e., mail contact). For example, the person interacting via mail cannot evaluate the trustee's physical appearance or their gestures, and might also lay a different focus on other attributes of the trustee (Sztompka, 1999).

3.6 The Act of Trust

While the antecedents of trust can range on a continuum (an object is perceived as higher or lower in trustworthiness), the act of trust is of binary nature: Either someone involves in an act of trust, or he or she does not. The act of trust results from the decision to trust, which in turn is affected by the perceived trustworthiness and the perceived risk. Mayer et al. (1995) defined trust as the willingness to make oneself vulnerable. This willingness can lead to a decision to trust which is a necessary condition to the act of trust. However, the decision to trust is not a sufficient condition to the act of trust (Blöbaum, 2016). Explicitly, as the decision to trust has been made, further risk *evaluation* occurs, followed by the final act of trust (Mayer et al., 1995). Only if a person acts, he or she becomes vulnerable. Consequently, the *actual* risk lies within the executed act itself. In the act of trust, the future is anticipated (Blöbaum, 2014), for example including assumptions about the consequences of the act of trust. Trusting acts also reveal information about a situation and the trustee. This information can be used for future evaluations. Therefore, trusting behavior was found to predict perceptions of trustworthiness in a longitudinal design (Alarcon et al., 2018).

3.7 Trust and Digitalization

Digitalization and the availability of technical devices such as smartphones have changed the way people work, live, and how they communicate with each other (e.g., Blöbaum, 2014; Latos et al., 2017). For example, people use computer programs to create sophisticated spreadsheets as a result of complex data analysis, and they use online chats to communicate. Traditional interpersonal and analogue communication shifts to communication *via* digital media, and also to communication *with* the media. According to Söllner et al. (2012), the technology can either be in (1) a *mediating* role in trusting relationships (Figure 25A), or the technology can be the (2) *trusted object (the trustee)* itself (Figure 25B).

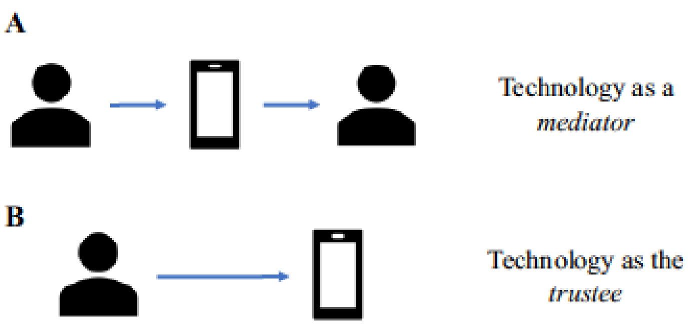


Figure 25. Technology (A) as a mediator; (B) as the trustee, adapted from Söllner et al. (2012).

First, the technology can be used as a *mediator* in interpersonal communications. For example, a smartphone (e.g., an online chat) is used to communicate with another person (i.e., the trustee). Moreover, cues used to evaluate the trustworthiness in interpersonal relations (i.e., appearance, gesture) become obsolete. In digital contexts, the evaluation of trustworthiness changes. For example, reputation and expertise of internet news providers were found to influence the assessment of trustworthiness (Flanagin & Metzger, 2007).

Second, the technology can be the *trusted object* itself. For example, a smartphone (e.g., a fitness app) is used to enter information (e.g., about food consumption) and is therefore provided with personal data. In turn, the smartphone delivers direct information and feedback about covered running distance, calorie consumption, etc. (Söllner et al., 2012; Figure 26).

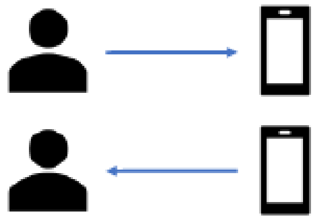


Figure 26. Visualization of the communication between a person and a smartphone.

As forms and environments of communication and trust change, so do new forms of trust and risk emerge. According to general definitions of trust, trust is the willingness to be vulnerable under risky conditions (Mayer et al., 1995), and is considered crucial in any situations that are associated with risks or uncertainty (Luhmann, 1979; Schoorman et al., 2015). Therefore, it has been argued that the concept of trust can be applied to communication contexts beyond interpersonal relations, i.e., in communication with technology or IT artefacts (Lee & See, 2004; McKnight et al., 2011; Söllner et al., 2012).

Communication via digital media comes along with new forms of risks: People depend on persons they have not met in person, explicitly they have not shared experience with (Flanagin & Metzger, 2007). Furthermore, limitations in data security, such as hacker attacks (e.g., Barcena et al., 2014) and issues with data reliability pose risks. Therefore, trust is required in the context of digital media usage. Also, progress in media changes rapidly, providing small starting points of experience to build upon, as experience is seen as an important contributing factor of trust.

At the same time, digitalization also facilitates access to knowledge and experience and therefore creates transparency. Users are provided with possibilities to control, and therefore to reduce risks. Thus, transparent information can function as a control system that bridges the difference between trust and risk by lowering the perceived risk (Schoorman, Mayer, & Davis, 2007). Also, new forms of risk evaluation emerge. For example, possibilities of interpersonal exchange or user evaluations create the opportunity to collect large amounts of (second-hand) information and knowledge about a trusted object (Blöbaum, 2016).

Thus, as communication, work, and living environments change with digitalization, so the requirement is raised to adapt models of trust to new forms of digital communication (McKnight et al., 2011; McKnight & Chervany, 2006; Söllner et al., 2012). For example, McKnight et al. (2011) postulated that trust is an important influencing factor in the technology usage as persons rely on technologies while facing various risks. Therefore, the need arises to establish an application of the traditional interpersonal concept of trust into the context of a digitized world. Therefore, traditional concepts of interpersonal trust focusing face-to-face interactions (e.g., Mayer et al., 1995) needed to be adapted to the digital and non-face-to-face, and from the personal to the impersonal context.

3.8 Trust in Technology

Digital interpersonal communication is present in multiple fields, such as in social media, in virtual working groups, or in online vending (Gefen & Straub, 2000, 2004; Jarvenpaa, Tractinsky, & Vitale, 2000; Kim, Ferrin, & Rao, 2008). Thus, digital interpersonal trust relationships have been examined in previous research, for example targeting interpersonal trust in social networks (Abrams, Cross, Lesser, & Levin, 2003) or laypeople's trust in experts in an online context (Hendriks et al., 2015). Also, trust in vendors in e-commerce has been examined in diverse studies (Gefen & Straub, 2004; Jarvenpaa et al., 2000; McKnight, Choudhury, & Kacmar, 2002). In contrast to interpersonal relationships *via* technology, trust can also relate to the technology or IT artefact itself (Söllner et al., 2012).

Nevertheless, human-technology interactions are dissimilar to interpersonal interactions (Lee & See, 2004; McKnight et al., 2011). Explicitly, technology does not act on the basis of volition, moral, or affect. Therefore, several modifications of traditional models describing interpersonal trust were necessary. However, research has also indicated that reactions to computers are similar to reactions to other humans, and that humans respond socially to technology (Lee & See, 2004; Reeves & Nass, 1996). Moreover, aspects of trustworthiness changed in their individual contribution. Other aspects with a strong relation to human behavior (e.g., benevolence) had to be redefined and applied to a non-human context. The approaches introduced below attempted to realize these points. In doing so, different conceptualizations of trust were established and were based on various technologies, ranging from specific IT artefacts of computer applications to large production plants.

3.8.1 Integrated Model of Human Trust in Machines. Trust in a technology was first described and examined in the late 1980's and the early 1990's (Muir, 1987, 1994) from a sociological perspective. The technologies targeted in this research were mainly large machines, such as production machines or production plants (e.g., milk pasteurization plants; Muir, 1994). The research was grounded in the assumption that automated systems, such as large machines were complex, large, and dangerous. Hence, Muir (1987) stated that either a sufficient control mechanism or trust in the automated system was necessary to transfer the work process from manual to automatized action. According to Muir (1987), trust in automation manifests on several stages that occur in a fixed order. The three stages were adapted from the conceptualization of interpersonal trust relations that has been described by Rempel et al. (1985; Figure 27).

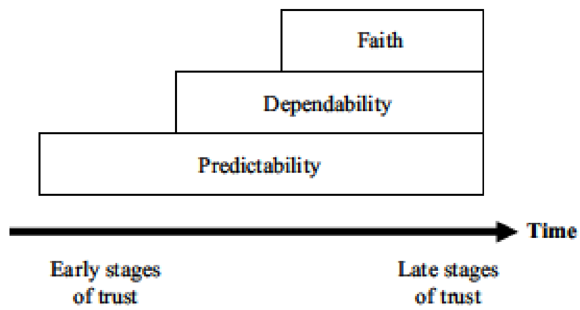


Figure 27. Sequential model of trust established by Rempel et al. (1985) and adapted by Muir (1987).

At early stages, (1) *predictability* is present. The more deterministic a machine is, the smaller are the degrees of freedom of this machine, and the higher is its predictability. Therefore, highly predictable machines and systems are observable and transparent. With some degree of experience, (2) *dependability* emerges. Dependability requires experience with a machine. Going beyond its predictability, dependability also includes the evaluation of risk and vulnerability of a system. Later, (3) *faith* dominates. Faith refers to the belief that the system will continue to act in the future as it has acted in the past. Hence, faith represents a generalization of past experience to future situations. The model of trust in automation has been applied to computer-controlled simulation of milk pasteurization plants and nuclear power plants (Lee & Moray, 1994; Muir & Moray, 1996).

3.8.2 Model of Human-Machine Interactions. The integrated model of human trust in machines entailing the factors predictability, dependability, and faith was later adapted to a model of human-machine interactions (Lee & Moray, 1992). The content of the factors was translated to similar factors that were labelled performance, process, and purpose. However, Lee and Moray (1992) assumed that the relation between these factors is not dynamic. In contrast to Muir (1987), Lee and Moray (1992) argued that faith is not a characteristic that develops at later stages of interaction, because persons usually learn early about the intended use of a technology (as represented in the faith dimension). Furthermore, Muir (1994) found that the dynamic sequence that is delineated in the original model (Rempel et al., 1985) is not applicable to the technology context. Moreover, predictability, dependability, and faith can also occur in different sequences. Therefore, Lee and Moray (1992) identified the necessity to modify the integrated model of human trust in machines and to translate the factors—that had been adapted from interpersonal relations—to the technology context. As general bases of trust, performance, process and purpose were identified (Figure 28).

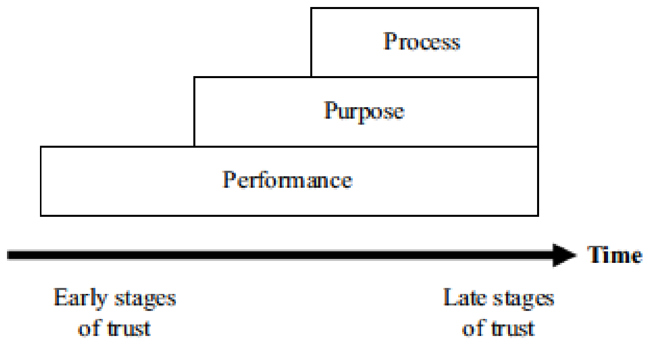


Figure 28. Sequential model of trust in automation, adapted from Lee and Moray (1992).

(1) *Performance* refers to the competence or ability of an automation and describes how capable the automation is to accomplish the user's goals. Performance also includes attributes of predictability and reliability. (2) *Process* refers to *how* the automation works, for example whether the algorithms are appropriate for the context of usage. Thus, the process dimension can also be regarded as understandability. (3) *Purpose* describes *why* an automation was developed. It is assumed that high purpose reflects that the trustee—in this context the automation's designer—has a positive motive towards the user. Purpose also describes the usage of an automation in a domain it was designed for. The model of human-machine interactions was tested via linear regression analyses on the field of a milk pasteurization production plant (Lee & Moray, 1992).

3.8.3 Model of Trust in Automation. Later, Lee and See (2004) reviewed the literature on trust research and proposed a complex conceptual and dynamic model of trust in automation that includes stages of trust, contextual aspects, and cognitive and affective processes within the trustor (Figure 29).

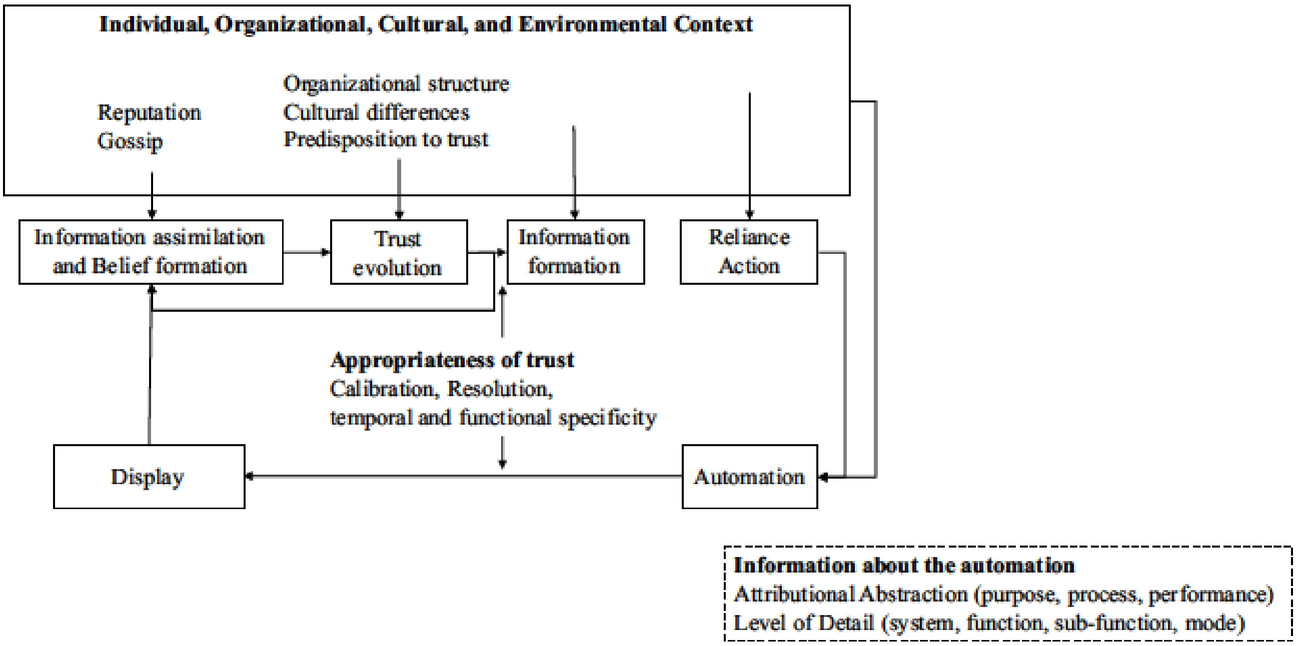


Figure 29. Model of Trust in Automation, adapted from Lee and See (2004).

As a starting point, automation was defined as a "technology that actively selects data, transforms information, makes decisions, or controls processes" (Lee & See, 2004; p. 50). In the model, aspects of trusting beliefs (information assimilation and belief formation) lead to intentions (intention formation), and action (reliance action). In turn, the interaction with an automation provides information about the automation that can be used for future belief formation. This information is displayed in the automation to a certain degree and is also assimilated based on affective and cognitive processes described below.

3.8.3.1 Information and belief formation. Belief formation (i.e., the perceived trustworthiness of an automation) is based on the trustor's evaluation of the automation's capability. The information processing about the automation is guided by (1) the trustor's goal-oriented characteristics and (2) cognitive processes. First, the goal-oriented characteristics of the trustor are *purpose, process,* and *performance*. These characteristics are adapted from previous models describing trusting beliefs in interpersonal and human-machine interactions (Lee & Moray, 1992; Muir, 1987; Rempel et al., 1985). The dimensions of performance, process, and purpose are comparable to ability, benevolence, and integrity defined in the integrative model of trust (Mayer et al., 1995). Second, the cognitive processes are divided into *analytic, analogical*, and *affective* processes. *Analytic* processes refer to the assumption that humans make choices that are knowledge-based and are result of a rational assessment of costs and benefits (Lewicki & Bunker, 1996). *Analogical* processes refer to second-hand information that lies beyond one's experience. Analytical processes entail reputation, gossip, but also reflect the integration of rules and social norms (Rasmussen, 1983). Affective processes are considered to play a crucial role in decision making, even though information and cognitive resources are available to generate a calculus-based choice (e.g., Damasio, Tranel, & Damasio, 1990).

Also, the level of detail (i.e., the abstraction level of cognitive processing) is of relevance: The information about the automation can be processed on different levels of detail. These levels range from a low detail level including the entire system, over functions and sub-functions, and finally to a high detail level including specific modes of an automation. In total, analytic, analogical, and affective processes influence the evolution of trust and promote appropriate trust.

3.8.3.2 Contextual factors. On all stages, these factors are influenced by individual, organizational, cultural, and environmental contexts. At early stages, second-hand information such as reputation and gossip affect the belief formation. This stage is similar to Lewicki and Bunker's (1996) concept of calculus-based trust. During trust evolution, other contextual factors such as organizational structure, cultural differences, and the predisposition to trust are relevant.

3.8.3.3 Overtrust and distrust. Going beyond other models describing trust in technology, the authors also specified different qualities of trust that are a function of trust and the system's capability. These forms of trust are *overtrust* and *distrust*, and they result in misuse or disuse. *Misuse* is a result of *overtrust* which refers to inappropriate reliance in technology, for example because the technology is not working adequate. In contrast, *disuse* refers to non-reliance that is based on *distrust*. Distrust explicitly means that trust falls short of a system's capabilities, and therefore the technology is rejected despite of potential capabilities.

3.8.3.4 Appropriateness. Furthermore, the appropriateness of trust is introduced (Lee & See, 2004). Appropriateness of a technology usage is based on previous experience with a technology's usage and influences the intention formation of future usage. The appropriateness is defined as a function of the congruence between trust and the capabilities of automation, resulting in misuse or disuse. More specifically, the appropriateness divides into calibration, resolution, and specificity. *Calibration* describes the correspondence between trust and the technology's actual capability. Therefore, calibrated trust means that trust matches the system capabilities and leads to appropriate trust. *Resolution* reflects how precisely changes in the capability of a technology change a person's trust evaluation. High resolution is associated with appropriate usage. *Specificity* describes the degree of how specific a person's trust evaluation is, in terms of temporal and functional details. Low specificity means that a person considers aspects of the whole system or over long time periods, whereas high specificity means that a person's trust evaluation refers to a technology's details or over a short time period. High specificity increases the likelihood that trust in an automation is appropriate as it is more sensitive to changes. Overall, high levels of calibration, resolution, and specificity shape appropriate usage of an automation, and therefore can mitigate misuse and disuse of a system. The model of trust in automation was provided as a framework theory and as a literature review that has not explicitly been tested in experimental designs. However, the comprehensive model integrates a variety of trust approaches from multiple disciplines and outlines important parallels as depicted in Table 4.

Table 4

Development of Trust in Technology Models Across Time and Across Scientific Perspectives

	Basis of Trust			Field of Study	Sequence	Specific Field of Study
Sociology Perspective						
Rempel (1985)	Predictability	Dependability	Faith	Trust in Humans	Sequence assumed	Interpersonal Trust
Muir (1987)	Predictability	Dependability	Faith	Trust in Technology	Sequence assumed	Trust in Machines
Lee & Moray (1994)	Performance	Process	Purpose	Trust in Technology	Sequence not assumed	Trust in Machines
Lee & See (2004)	Performance	Process	Purpose	Trust in Technology	Sequence not assumed	Trust in Automation
Söllner et al. (2012)	Performance	Process	Purpose	Trust in Technology	Sequence assumed	Trust in IT Artefacts
Psychology Perspective						
Mayer et al. (1995)	Ability	Integrity	Benevolence	Trust in Humans	Sequence not assumed	Interpersonal Trust
McKnight et al. (2011)	Reliability	Functionality	Helpfulness	Trust in Technology	Sequence not assumed	Trust in Technology

Note. Models in non-technology specific context served as a theoretical foundation of trust in technology models, as indicated by grey font color; blue arrows, visualization of the model development across time.

3.8.4 Model of Trust in IT Artefacts. When computers and smartphones became popular, the humans' relation to automation changed from machines to smaller computers and smartphones. While previous models focused on large machines and production plants as the trusted objects (e.g., Lee & Moray, 1992; Muir & Moray, 1996), such models had not been tested on the field of computers as direct interaction partners so far. Söllner et al. (2012) stressed that a range of studies had focused on the *mediating* role of IT artefacts (e.g., computers) when examining trust in digital contexts. For example, the computer holds a mediation role when a person communicates and trusts another person *via* the computer. In contrast, Söllner et al. (2012) aimed at developing a model of trust in an IT artefact, in which the IT artefact holds the role of the *trustee*.

In doing so, Söllner et al. (2012) used the dimensions *performance, process,* and *purpose* as guiding factors that had been established, tested, and reviewed previously (Lee & See, 2004; Lee & Moray, 1992). As the three dimensions were assumed to be of sequential nature, Söllner et al. (2012) aimed at capturing and testing this assumption via an adequate statistical model. Therefore, a formative first-order, formative second-order model was established with trust as an endogenous latent construct with reflective indicators and the three dimensions as separate exogenous latent constructs with formative indicators (Figure 30).

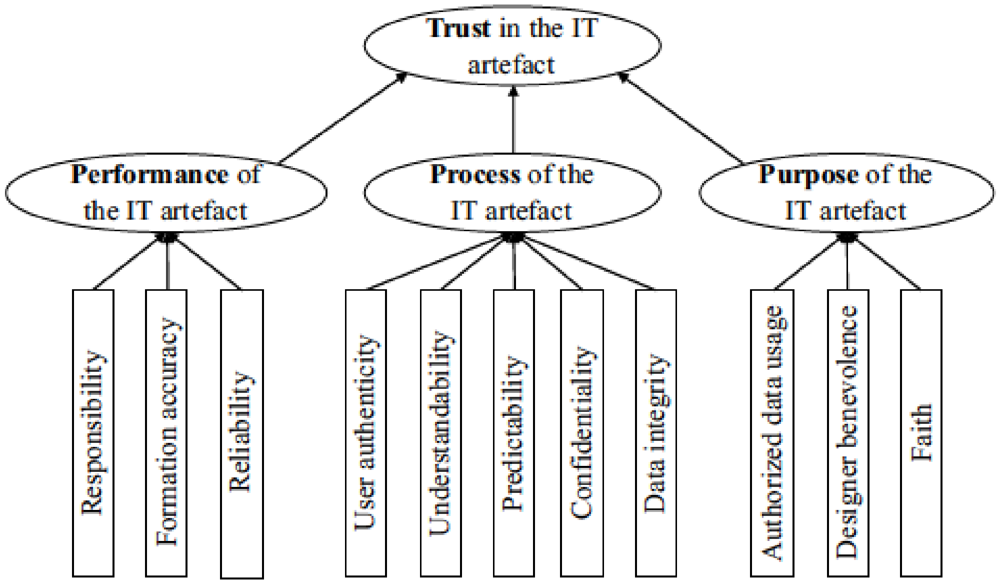


Figure 30. Model of trust in IT artefacts, adapted from Söllner et al. (2012).

The *performance* dimension includes three formative indicators (i.e., items), namely (1) responsibility (the artefact has all necessary functionalities); (2) information accuracy (the information is accurate); and (3) reliability (the artefact is reliable to perform a task). The *process* dimension includes five formative indicators: (1) user authenticity (no unauthorized person can use the artefact); (2) understandability (it is understandable how the artefact works); (3) predictability (how predictable the next action is); (4) confidentiality (the user can control who is able to access the data); and (5) data integrity (personal data cannot be changed by unauthorized). The *purpose* dimension includes three formative indicators: (1) authorized data usage (the data is only used in its intended purpose); (2) designer benevolence (the designer has the users' interests in mind); and (3) faith (the user can rely on the artefact in the future). The model was tested on the field of general IT artefacts and was analyzed using Partial Least Squares (PLS) regressions. The results indicated good construct validity. The model has been applied to explain IT usage, such as self-adaptive apps and mobile-learning apps (Evers, Kniewel, Geihs, & Schmidt, 2014; Lehmann & Söllner, 2014).

3.8.5 Model of Trust in Technology. McKnight et al. (2011) established a comprehensive model to explain post-adaptive usage of a specific technology from a psychological perspective. The model is referring to the psychological perspective on trust, regarding the trustor's perceptions of the trustee's attributes. By laying focus on trusting beliefs in the technology itself, it was assumed to gain a more precise understanding about what makes a technology trustworthy, instead of focusing on persons or contexts associated with such usage (McKnight et al., 2011). The trust in a specific technology model is rooted in previous work on prominent and well-established conceptualizations of interpersonal trust and distrust as well as trust in e-commerce contexts (Mayer et al., 1995; McKnight & Chervany, 2001; McKnight et al., 2002). The trust in a specific technology model was established and tested on the field of specific computer programs, explicitly referring to a spreadsheet program (Excel).

3.8.5.1 Stages of trust. The trust in technology model was conceptualized as a model explaining post-adaptive usage of technology. Post-adaptive usage is defined as the state after a specific technology "has been installed, made accessible to the user, and applied by the user in accomplishing his/her work activities" (Jasperson, Carter, & Zmud, 2005; p. 531). Herein lies a distinction to the integrative model of trust proposed by Mayer et al. (1995). Mayer et al. (1995) state that their model can be applicable to situations before an act of trust has occurred, and also before the trustor has experienced an interaction with the trustee. Differentiating between stages of trust, these forms of trust are also marked as *initial trust* that is comparable to Lewicki et al.'s (2006) calculus-based trust. Therefore, initial trust is assumed to be mainly predicated on cost vs. benefit assessments. In contrast, *knowledge-based trust* requires experience with the trustor, and therefore allows the trustor to establish a more elaborate estimation about the trustee's attributes, allowing more stable predictions about the trustee's behavior in a specific situation that is relevant to the trust context (Lewicki et al., 2006; McKnight et al., 2011). Therefore, research focusing on initial trust (i.e., cost vs. benefit assessment) in the IT context has demonstrated less predictive validity than the assessment of knowledge-based trust (Kim & Malhotra, 2005). Herein also lies a difference compared to the TAM (Davis, 1989). Whereas the TAM perspective focuses on perceived usefulness and ease, knowledge-based trust is going beyond the benefits of a technology, also considering risks related with usage and specific external factors influencing the beliefs about a technology (e.g., institutional and contextual factors).

McKnight et al. (2001) differentiated between three sets of trusting beliefs varying in their degree of context and their degree of technology specificity. The three sets are *propensity to trust*, *institution-based trust*, and *trusting beliefs* in a specific technology (Figure 31).

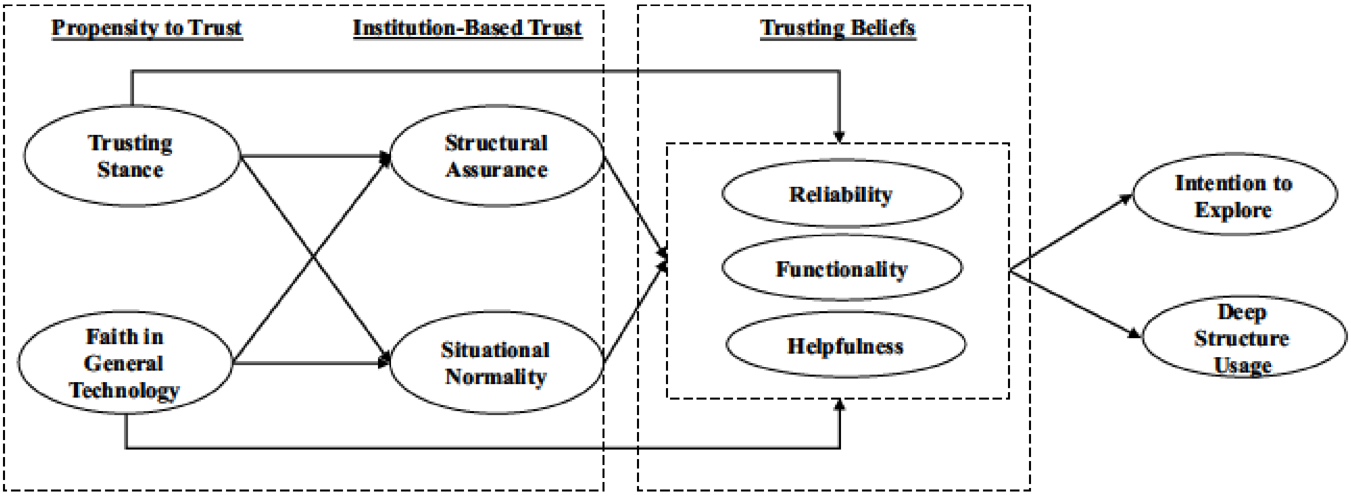


Figure 31. Model of Trust in a Specific Technology, adapted from McKnight et al. (2011).

3.8.5.2 Propensity to trust. Propensity to trust is a non-specific individual difference that lies within the trustor and describes the willingness to rely on a technology across different technologies and situations. Propensity to trust is comparable with the trustor's propensity described in the integrative model of trust (Mayer et al., 1995), and therefore is regarded as individual difference that is more dynamic than a stable trait (Mayer et al., 1995; McKnight et al., 2011). Furthermore, propensity to trust is not technology or situation specific. Propensity to trust is divided into faith in general technology and trusting stance.

Faith in general technology describes general beliefs about a technology and about how it works. Specifically, faith in general technology means that technology is perceived as reliable, functional, and helpful. *Trusting stance* represents the belief that using a technology and relying on a technology has a positive impact and will lead to positive outcomes. Together forming propensity to trust, faith in general technology and trusting stance lead to institution-based trust.

3.8.5.3 Institution-based trust. Institution-based trust is a more situation specific construct that is described as the belief that supportive situations and structures positively influence successful technology usage. Thus, institution-based trust refers to a concrete class of technology within a more specific situational context compared to propensity to trust. Institution-based trust describes the assumption that certain characteristics and situations connected to the use of a technology will lead to successful use of this technology. Institution-based trust is not directly represented in the integrative model of trust (Mayer et al., 1995), and is rather derived from previous research on organizational relationships (McKnight et al., 1998). Institution-based trust is divided into *situational normality* and *structural assurance*.

Situational normality describes the belief that the use of a new specific technology in a certain situation is perceived as normal and pleasant. Using the technology in a new way is perceived comfortable. For example, if working with spreadsheets is perceived as normal, this form of trust would be transferred when working with spreadsheets in a specific computer program application. *Structural assurance* describes assumptions about the support and infrastructure associated with the specific technology. Structural assurance refers to the belief that adequate consumer rights, data security, or replacement exist to warrant uncomplicated and safe usage. Structural assurance is assumed to be connected with confidence in a technology, therefore leading to trust in a specific technology. Institution-based trust is assumed to mediate the connection between propensity to trust and trusting beliefs in a specific technology.

3.8.5.4 Trusting beliefs in a specific technology. Trusting beliefs in a specific technology are technology specific and refer to a trustor's relationship with a specific technology. Trusting beliefs in a specific technology describe a set of characteristics that are associated with the object of dependence. Trusting beliefs represent the trustor's assumptions about beneficial characteristics that are associated with a specific technology, thus representing the perceived trustworthiness of a technology. Trusting beliefs in a specific technology are summarized in a superordinate second-order construct, reflected by three manifest factors. In adaption to a model describing perceived trustworthiness in interpersonal relations (Mayer et al., 1995), the three factors were adapted to the technology context and identified as functionality, helpfulness, and reliability.

Functionality was adapted from the ability factor in interpersonal relations (Mayer et al., 1995). While ability refers to a set of competencies that are attributed to a trustee, functionality represents the belief that a technology has the capacity to fulfil a required task. The capacity to fulfil this task is based on the technology's functions, features, and capability. The functionality factor was also adapted from conceptualizations describing trust and distrust in interpersonal relations and in e-commerce contexts (McKnight & Chervany, 2001; McKnight et al., 2002).

Reliability was adapted from the integrity factor in interpersonal relations (Mayer et al., 1995) and predictability in interpersonal and e-commerce situations (McKnight & Chervany, 2001; McKnight et al., 2002). Integrity describes the trustee's adherence to principles the trustor considers adequate. Predictability refers to the consistence of the trustee's actions, leading to predictableness of his/her actions. In the technology context, reliability represents the belief that a specific technology is precise, consistent and is predictable in its progress.

Helpfulness was adapted from benevolence which was conceptualized in both models of interpersonal and e-commerce trust (Mayer et al., 1995; McKnight & Chervany, 2001; McKnight et al., 2002). Benevolence is an attribute that describes a component that is related to interpersonal contact. It refers to the belief that the trustee wants to do good for the trustor and is interested in acting in the trustor's interest. In contrast, technology is not a social being, and accordingly neither acting on the basis of volition nor experiences emotions such as empathy. However, benevolence was adapted to the technology context by defining it as helpfulness. Helpfulness refers to the supply of a help function of the technology that provides adequate and reactive support when it is required. Therefore, helpfulness depicts the help function as an implementation of a user support system that also roots in the benevolence of the app providers support section and their staff (McKnight et al., 2011).

The model of trust in a specific technology has been tested by McKnight et al. (2011), indicating good construct validity. In further analyses within this study, trusting beliefs in a specific technology predicted both the intention to explore a specific technology, and to practice deep structure usage of a specific technology.

Trust in technology is assumed to change over time, just as trust has been approached by a range of scholars (e.g., Lee & Moray, 1992; Lewicki & Bunker, 1996; McKnight et al., 2002; Söllner et al., 2012). Therefore, McKnight et al. (2011) implied the necessity to differentiate between different stages of usage when investigating trust in technology (e.g., non-usage, usage or post-adaption, and post-usage or dropout). In doing so, comprehensive and precise analysis of trust related beliefs and its impact on adoption and maintenance of technology usage is possible. Yet, the model of trust in technology (McKnight et al., 2011) has not been tested on the field of new technologies (e.g., smartphone apps).

3.9 Trust and Control

In the context of risk management systems, the influence of control has been discussed by various scholars (Muir, 1994; Rempel et al., 1985; Schoorman et al., 2015). Examining trust in automated systems (e.g., production plants), the transfer of control to a machine was identified as a matter of trusting (Muir, 1994). The necessity of supervisory control was also mentioned by Sheridan and Hennessy (1984) in the context of evolving trust in large machines. In a more elaborate way, control was considered as a bridge function between trust and risk (Schoorman et al., 2015). Schoorman et al. (2015) introduced a *bucket model* specifying the assumed relations between risk, trust, and control systems (Figure 32).

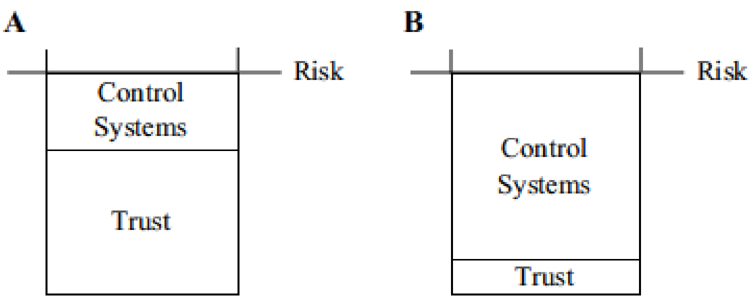


Figure 32. Bucket model specifying the associations between trust, risk, and control systems, adapted from Schoorman et al. (2015).

If the perceived risk exceeds the trust, the gap between trust and risk can be bridged via a control system. Thus, the risk is reduced to an acceptable level, and one can engage in the act of trust. If trust is high, only little control is needed to bridge the gap. Conversely, if trust is low, much control is needed to bridge the gap between trust and risk. For example, a manager who does not trust his employees to work properly would extensively use unannounced calls or time sheets as control mechanisms to bridge the gap between risk and low trust. In contrast, a manager who trusts his employees to work properly would not survey his employees' work and working times.

3.10 Trust and Risk

In the most widely used definition of trust, trust is the willingness to make oneself vulnerable under risky conditions (Mayer et al., 1995). Therefore, risk is a concept that is directly connected to trust. Furthermore, works reviewing the literature on trust theories identified a consensus that trust and risk are strongly interrelated concepts (Blöbaum, 2016; Mayer et al., 1995; Rousseau et al., 1998). Blöbaum (2016) summarizes that the relation between trust and risk is of circular nature: Only if a person trusts, this person can engage in a potentially risky act, and only if a risk exists, a person can trust. In contrast to general risk propensity, the risk perception is situation specific and always relates to a concrete situation.

However, as conceptual differences in trust definitions exist, so do different approaches exist defining how trust and risk are related. When it comes to defining trust, Mayer et al. (1995) emphasize the aspect of the willingness to be vulnerable facing risks. Bradach and Eccles (1989, p. 104) define trust as "a type of expectation that alleviates the fear that one's exchange partner will act opportunistically". From this point of view, trust is regarded as a function that diminishes a perceived risk in the relationship with a trustworthy party. Perceived risk is often conceptualized as the function of two important components, of uncertainty and adverse consequences (Bauer, 1960; Cunnigham, 1967; Dowling, 1986; Jacoby & Kaplan, 1972; Jaeger, Webler, Rosa, & Renn, 2013). While some scholars argue that trust has no influence on risk perception, others regard trust as a mechanism that reduces trust (as described below). Other authors argue, that trust and risk perception are mirror images of each other (Das & Teng, 2004). In this case, perceived trustworthiness would affect both risk perceptions and trust itself.

3.10.1 Trust with no influence on risk perception. Many scholars conceptualize perceived risk or uncertainty as a *precondition* for trust (Eckel & Wilson, 2004; Luhmann, 1979; Mayer et al., 1995; McKnight & Chervany, 2001). Therefore, a person *first* perceives trustworthiness. In combination with the perceived risk, a trustor then decides to take this risk. Mayer et al. (1995) claim that trust has no influence on risk perception. Risk is rather assumed to moderate the association between trust and trusting behavior: The higher the perceived risk, the more trust—i.e., the willingness to take a risk—is needed in the relationship with the trustor.

3.10.2 Trust as a mechanism to reduce risk perception. However, other scholars consider trust as a *mechanism* that reduces the risk perception itself, and therefore influences the risk perception (Das & Teng, 2001; Kim et al., 2008; Kunnel, 2017; Lewicki et al., 2006). Hence, if persons trust the other party, they perceive a smaller risk to face negative outcomes, and therefore they are more likely to interact with this other party.

Since consumer behavior—as any decision-making—involves risk (e.g., Bauer, 1960), the perception of risk has been broadly examined in the area of consumer research. This latter relationship is considered and tested in many studies in the online context, such as e-commerce (Jarvenpaa et al., 2000; Kim et al., 2008; Mitchell, 1999; Pavlou, 2003), mobile banking (Luo, Li, Zhang, & Shim, 2010), or social media platforms (Wang, Xu, & Chan, 2015). In the area of consumer research, many authors argue that a high level of trust reduces the perceived risk (Jarvenpaa et al., 2000; Kim et al., 2008; Mitchell, 1999).

3.10.3 Dimensions of risk. Perceived risk is regarded as a dimension specific construct (Cunnigham, 1967; Dowling, 1986). Based on a literature review, Jacoby and Kaplan (1972) identified five functionally different dimensions of perceived risk in purchased products: financial, performance, physical, psychological, and social risk. Additionally, an overall risk dimension was introduced, summarizing the total risk associated with a purchased product. The evaluation of risk was assessed in an assortment of products from recreational, health, and hygienic context that varied in price, visibility, and intimacy. The study was conducted based on questionnaires and the dimensions were identified using multiple regression analysis.

The risk dimensions were described as follows: (1) *financial risk* refers to the risk of losing money, either because it does not work or because it costs more than it should to keep it maintained; (2) *performance risk* is the likelihood that the product will not work properly or that there is something wrong with the product; (3) *physical risk* refers to possible detriments to the health, or that the product is not safe; (4) *psychological risk* refers to the incongruence with the self-image or self-concept of a consumer, explicitly the way people think about themselves; (5) *social risk* refers to the impression on other people, i.e., that the product usage affects the way others think of the user in a negative way; (6) *overall perceived risk* summarizes all sorts of factors about how risky the usage of a product would be. The questionnaire established by Jacoby and Kaplan (1972) demonstrated good validity and was also cross-validated in a second sample (Kaplan, Szybillo, & Jacoby, 1974).

Across products and situations, the risk dimensions can vary in their relative importance and degree. Thus, the importance of each dimension specifically depends on the context and the product (Jacoby & Kaplan, 1972; Kaplan et al., 1974). Also, in a certain situation, different dimensions of risk can be traded off against each other and therefore form different levels of overall perceived risk (Jacoby & Kaplan, 1972). For instance, a person paying for a fitness-app might take some financial risk, while the performance risk might decrease compared to an app that is free of charge. Furthermore, the same type of risk might be high and low at the same time. In the case of fitness apps, the physical risk for instance might be affected in two opposing ways. On the one hand, the risk of overweight and resulting problems and diseases can be reduced (Higgins, 2016; Schoeppe et al., 2016; West et al., 2012). On the other hand, doing an exercise wrong might cause physical damage (Kemler, Romeijn, Vriend, & Huisstede, 2018). Although the dimensions of risk can vary in a dynamic way, risk has often been measured as one overarching factor of perceived risk in studies in the online context (Featherman & Pavlou, 2003; Luo et al., 2010; Park, Lee, & Ahn, 2004). In these studies, the perceived risk had a negative impact on the behavioral intention or the actual behavior.

3.11 Trust, Risk, and Benefit

It is assumed that the formation of trusting intentions and behavior is guided by the assessment of costs and benefits (Lewicki & Bunker, 1996). Especially when the perceived trustworthiness of a trustee is based on little or no personal experience at early stages of trustor-trustee relationships, initial trust is present (Lewicki & Bunker, 1996; McKnight et al., 2011). In contrast to experience-based evaluations, benefit and risk assessments are dominant in the evaluation of trustworthiness. Therefore, when examining initial trust in digital environments (e.g., the influence of initial trust in web vendors on online purchase intentions), risk vs. benefit assessments are a crucial factor to consider and are of predictive value (Gefen, Karahanna, & Straub, 2003; Vance, Elie-Dit-Cosaque, & Straub, 2008).

Risk vs. benefit assessments are a central element in theories explaining decision making in economy, medical treatments, etc. (Davis et al., 1989; Lee, Chan, Balaji, & Chong, 2016; Lynd & O'Brien, 2004; Quah & Haldane, 2007). Also, risk vs. benefit assessments are a central element in the Technology Acceptance Model (TAM, Davis et al., 1989) and are represented by the perceived usefulness (i.e., the benefit) and the perceived ease of usage. The TAM has been successfully applied to explaining consumer intentions and decisions (Gefen & Straub, 2000; Szajna, 1996; Taylor & Todd, 1995). Furthermore, it has been argued that a strength of the TAM may be its ability to explain intentions and behavior especially in *early* stages of contact, i.e. after a brief time of interaction (Davis et al., 1989; Szajna, 1996).

Previous research targeting elaborate explanation of technology usage has gone beyond traditional trust research models, integrating both trusting beliefs and also the evaluation of risk vs. benefits. As depicted below, the TAM (Davis et al., 1989) was used as a major theory (Gefen et al., 2003; Kim et al., 2008). Also, perceived risk was regarded as an influencing factor in further research (Kim et al., 2008).

3.11.1 Model of Trusting Beliefs and TAM in Online Shopping. Gefen et al. (2003) argued that both perceived benefits of technology usage (as embedded in the TAM; Davis et al., 1989), but also potential risks (as embedded in trust concepts) are of relevance when explaining technology usage. Therefore, the authors used a set of trusting beliefs in addition to perceived usefulness and perceived ease of use derived from the TAM (Davis et al., 1989) to explain IT usage (i.e., online shopping). As antecedents of trust, calculative-based trust, institution-based structural assurance, institution-based situational normality, and knowledge-based familiarity were applied (McKnight et al., 2002). Gefen et al. (2003) found that trusting beliefs and trust influence intended use, but also lead to perceived ease of usage and perceived usefulness, which in turn positively influence the intended use (Figure 33).

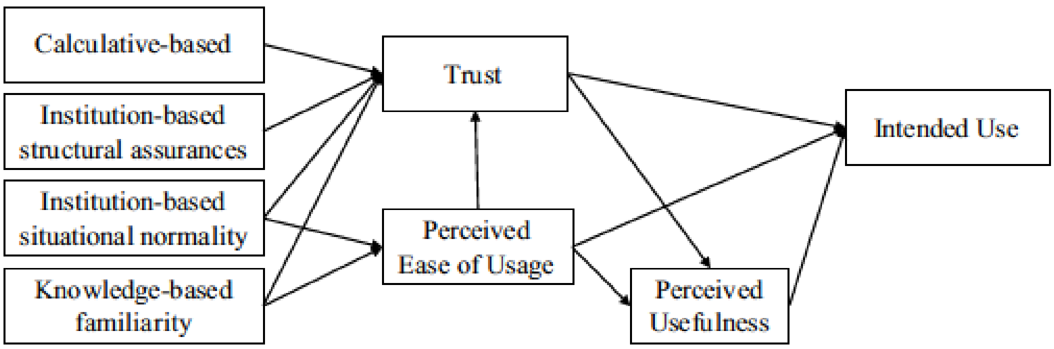


Figure 33. Integrative model of trust and TAM in Online Shopping, adapted from Gefen et al. (2003).

However, the associations between trusting beliefs, trust, perceived ease of use, perceived usefulness are of complex and interlaced nature. The results indicate that perceived benefit is an important element that is directly connected to trust and risk evaluation, and therefore to technology usage.

3.11.2 Model of Trust, Perceived Risk, and Benefit in E-Commerce. In the field of electronic commerce (e-commerce), Kim et al. (2008) identified a model explaining how trust, perceived risk and benefit affect the intention to purchase (Figure 34).

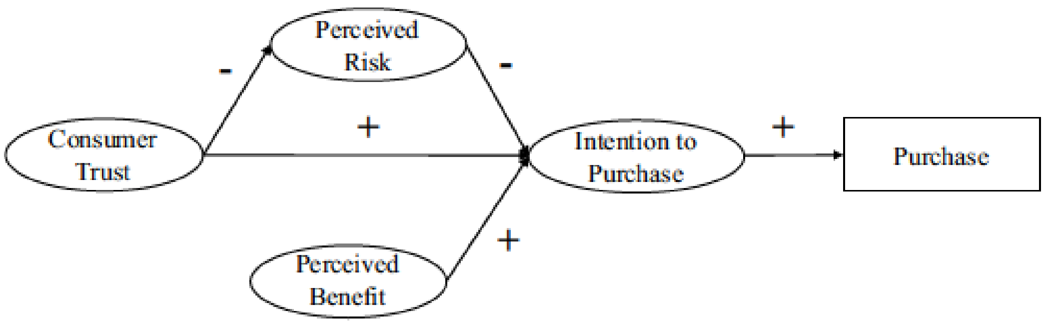


Figure 34. Model of trust, perceived risk and benefit in e-commerce, adapted from Kim et al. (2008).
Note: +, positive association; -, negative association.

Kim et al. (2008) used the Theory of Planned Behavior (Ajzen & Driver, 1992) and Theory of Reasoned Action (TRA; Fishbein & Ajzen, 1977)—theories the TAM was based on—as guiding frameworks for the conceptualization of intention and purchasing behavior. Kim et al. (2008) referred to the trust concept established by Mayer et al. (1995) measuring trustworthiness. To assess perceived risk, Kim et al. (2008) applied Jacoby and Kaplan's (1972) concept of dimensional risk, using a combination of items used in previous studies (Gefen, 2000; Jarvenpaa et al., 2000) and items created by the authors. To measure perceived benefit, a mix of items used in previous studies combined with self-created items was used.

In their study, Kim et al. (2008) conducted structural equation modelling (SEM), explaining how trust, perceived risk and benefit affect the intention to purchase and purchasing behavior. As presented in Figure 34, intention to purchase was negatively affected by perceived risk, and was positively affected by trust and perceived benefit. Furthermore, trust negatively affected perceived risk, indicating that perceived risk can be regarded as a mediator variable. In the SEM, a good model fit indicated validity for the proposed model, suggesting a mediating role of perceived risk between trust and intention to purchase.

In sum, previous research on the field of e-commerce indicates that the integration of perceived benefit and risk in theory building can lead to better understanding and explanation of intentions and behavior. In traditional models conceptualizing trust, benefit has scarcely been considered explicitly. However, a model integrating trust, risk, and benefit assessments has not yet been applied to the context of health-related technology, such as fitness apps.

Overall, this Chapter 3 provided insight into the theoretical foundation of trust research, including different approaches to trust and aspects within the nomological framework of trust. Applications of trust research to the technology context were presented, including the establishment of the trust in a specific technology model (McKnight et al., 2011). In the context of technology usage, risk and benefit assessments were identified as relevant factors. Also, newer models were presented that integrate trust theory with aspects of benefit and risk assessments. The interrelations between trust, perceived risk, and perceived benefit have neither been examined in the field of technology applications nor with regards to fitness app usage yet, and are therefore of high interest. The following Chapter 4 will focus on a novel aspect of trust associated with fitness app usage, i.e., body trusting.

4. Self-Tracking and Body Trusting

Fitness apps can provide diverse body related information (e.g., covered steps and distance associated with physical activity, calories burned; West et al., 2012), and thus offer objective feedback regarding body-related processes and states. In Chapter 2 it has been outlined that fitness app usage is associated with a range of benefits (e.g., supporting health behavior) and risks (e.g., data insecurity, loss of privacy), indicating that trust can be an important aspect in fitness app usage. Also, fitness app usage is a means of self-tracking, and contributed to the establishment of the quantified self-movement (Nafus & Sherman, 2014). Within the quantified self-movement, self-tracking via digital media (e.g., via fitness apps) has been described as a means to practice body awareness and body trusting (e.g., Sharon & Zandbergen, 2017). As introduced in Chapter 3, body trusting—i.e., the body as an object of trust—emerges a potentially novel form of trust.

Consequently, this chapter brings together the applications of digital technology—specifically fitness apps—and trust concepts introduced in the chapters before. First, the general practice of self-tracking and its forms are introduced. Later, the special characteristics of self-tracking via digital media are outlined, presenting both risks and benefits associated with self-tracking via digital media. A specific focus is laid on the tracking and feedback functions within fitness apps and wearable devices. In a next step, the quantified self is introduced. In this context, an integrative model of body awareness is presented, including the aspect of *body trusting*. Body trusting and the identification of the role of trust in body trusting represent key elements of this work. Hence, the development of the questionnaire and items measuring body trusting are presented in detail. Overall, Chapter 4 sheds light onto the fields of risk and benefit (i.e., trust), their application to body and health, and their overlap, representing body trusting (Figure 35).

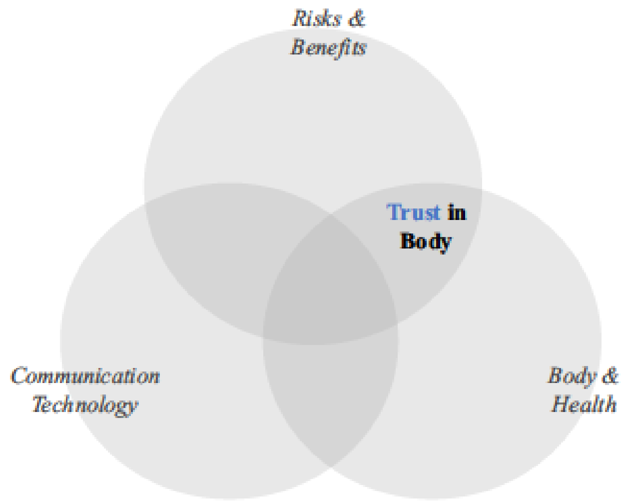


Figure 35. Visualization of body trusting as an intersection of health and the integration of risks and benefits targeted in this chapter.

4.1 Self-Tracking

The practice of self-tracking means that a person is keeping track of certain parameters. Self-tracking can occur in one's mind, on a piece of paper, and via digital devices, such as smartphones and apps designed to track specific parameters (Barcena et al., 2014; En & Pöll, 2016). Traditional practices of self-tracking can be traced back into the ancient Greek and Rome when people documented their mental and body states, which was also described as *self-writing* (En & Pöll, 2016; Foucault, 1997). In present times, most people engage in some tracking activities of multiple parameters and via diverse media. For example, in a survey including more than 3,000 participants from the U.S., it was found that 69% of the participants tracked a health indicator for themselves or for others (Fox & Duggan, 2013). Most participants tracked the health indicators in their minds/heads (49%), 34% stated to track the data on paper (e.g., in a diary), and 21% used a technology (e.g., a smartphone app) to track their data (Figure 36).

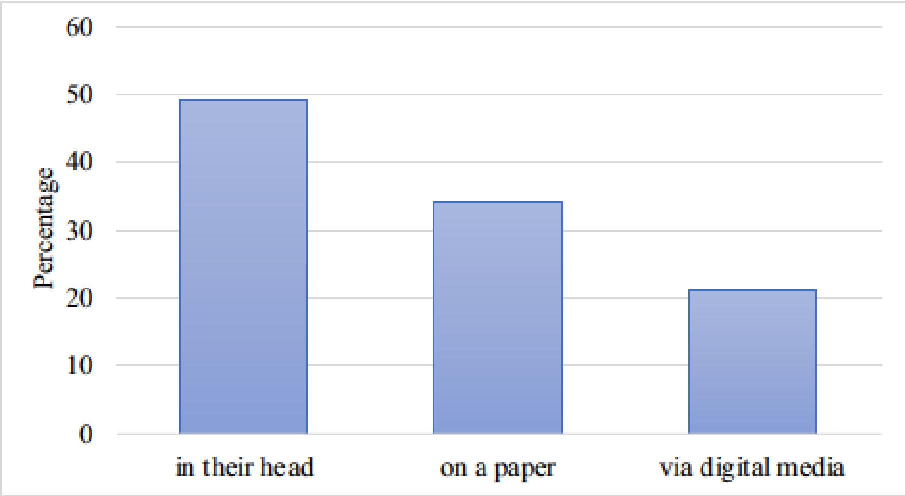


Figure 36. Tracking practice of health-related information, adapted from Fox and Duggan (2013).
Note: Multiple answers were possible.

Tracking can either refer to subjective experience that is noted or estimated on a scale (e.g., mood), and can also refer to objective assessment via measurement tools. Objective feedback about body states can convey a perception of self-knowledge and control over the body (Crawford et al., 2015). These measurement tools can either be of analogue (e.g., a questionnaire, an analogue weight scale) or of digital (e.g., an electronic weight scale, a wearable device) nature.

The first prominent objective self-tracking measurement tool that was applied in daily life was the weight scale (Crawford et al., 2015). After weight scales had made their way from the medical doctor's room to public weight scales standing in the streets, weight scales could be bought for home use since the 1920's. Together with this new opportunity to track and control health related parameters in daily life, the promotion of health control (e.g., via weight scales) also became subject to the media in the U.S. This was the first time in the history of the U.S. that women were encouraged to diet (En & Pöll, 2016).

Tracking practices can be found across multiple domains, such as work, food, culture, learning, etc. (Albrechtslund, 2013). When it comes to self-tracking, there is a mass of subjects that can potentially be tracked, ranging from finance (e.g., spending) to mental states (e.g., mood), medical symptoms (e.g., headache), physiological states (e.g., weight), physical activity (e.g., running distance), bodily functions (e.g., fertility), and consumption, such as caffeine (Barcena et al., 2014). A detailed overview of parameters that can be tracked via smartphone apps is depicted in the next section. In a survey targeting health tracking, 60% of the participants stated to track their weight, diet, or exercise routine, 33% tracked any other health indicator (e.g., sleep pattern, pain, blood pressure), and 12% tracked health indicators for another person (Fox & Duggan, 2013), as presented in Figure 37.

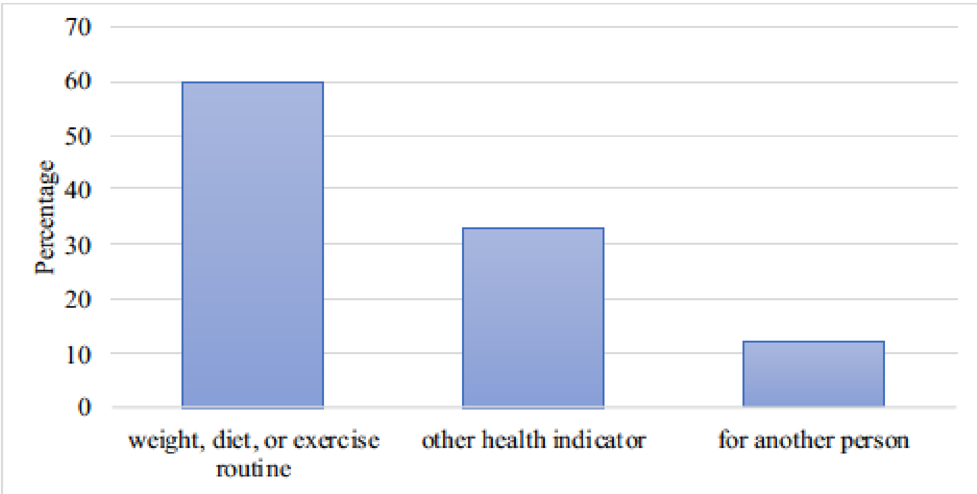


Figure 37. Tracking content of health-related information, adapted from Fox and Duggan (2013).
Note: Multiple answers were possible.

Especially in health, an increasing awareness of healthier living has developed among the public, producing a trend towards higher self-awareness (Barcena et al., 2014).

4.1.1 Types of self-trackers. In the field of health tracking, Fox and Duggan (2013) found that especially persons with chronic health conditions tracked health related data. Specifically, 62% of persons suffering from two or more chronic conditions kept track of their states, whereas 19% of persons not suffering from chronic conditions engaged in self-tracking. Furthermore, persons with chronic health conditions were more likely to use multiple (i.e., digital and non-digital) means for self-tracking. Half of the self-trackers (49%) were found to update their records only occasionally, especially when their conditions (e.g., health conditions) changed (Figure 38). 46% of the self-trackers stated to regularly track themselves. Most of these self-trackers did not share their data and 34% shared their data with other persons or groups, half of those shared their data with a professional clinician.

Figure 38. Tracking frequency and sharing behavior referring to health-related information, adapted from Fox and Duggan (2013).
Note: Multiple answers were possible.

Another type of self-trackers that has been described by Barcena et al. (2014) is the "sports enthusiast" who enjoys setting performance goals and is keeping track of his or her progress, finding out whether he or she is improving or not. It has been discussed that this behavior serves to gain social validation and yields to narcissistic tendencies in the society (Barcena et al., 2014).

4.1.2 Benefits of self-tracking. Devices designed to practice self-tracking have been subject to advertisement and media presence since the first weight scales were offered. Slogans such as "He who often weighs himself knows himself well. He who knows himself well lives well." (Crawford et al., 2015, p. 486) implies an epistemological benefit: self-knowledge leads to higher levels of well-being and quality of life. In the present times, providers of fitness wristbands use similar slogans such as "This device can know me better than I know myself and can help me be a better human" (Crawford et al., 2015, p. 488). In sum, the media and specifically health product providers have contributed to the perception of why self-tracking can be beneficial for us. Specifically, it has been conveyed that self-tracking is of epistemic value and can enhance the quality of life.

Apart of lifestyle applications, tracking of health status has been used in the treatment of diseases (e.g., food or symptom protocols in allergy or pain treatment). Overall, 46% of the persons tracking their health status believed that this practice has changed their approach to maintain their health, and 34% stated that self-tracking has affected a decision about the treatment of an illness or a health condition. In scientific research, self-tracking has been demonstrated to be a beneficial tool for health improvement. Shull, Jirattigalachote, Hunt, Cutkosky, and Delp (2014) found that self-tracking can be helpful to evaluate movement disorders and the outcomes of interventions, such as surgery. Real-time tracking tools have also been applied to track trajectories of symptoms, and have promoted improvements in patient's symptom management compared to the analysis of retrospective data. Patel, Klasnja, Hartzler, Unruh, and Pratt (2012) conducted a study with cancer patients tracking their symptoms, and found better identification of symptom patterns, improved symptom communication with the clinicians, and improved psychological comfort in the patients compared to a control group.

The reasons why people engage in self-tracking are assumed to be about finding patterns in one's behavior, about causes and trajectories of a disease or unhealthy behavior, and physical inactivity (Moschel, 2013). The implication of these issues is that human life is risky. Specifically, these risks can involve physical dysfunction, disease, and also social risks such as failing to meet social norms and standards (En & Pöll, 2016). Furthermore, human perception is based on subjective and biased feelings and memory, being of risk to be untrustworthy. Hence, self-tracking is described as a means to practice *control*, consequently leading to risk reduction. In this context, digital media can provide a tool to produce "hard facts" and a more objective perception of the self (En & Pöll, 2016, p. 44). Consequently, self-tracking can serve as a strategy to deal with the risk of human inadequacy.

4.2 Self-Tracking via Digital Media

Self-tracking via digital media means "recording (mostly quantitative data) about aspects of one's self (or selves) with the aid of digital technologies" (En & Pöll, 2016, p. 38). It contributes to the development of the web 2.0 described in Chapter 2 (Davis, 2012), implicating that users actively contribute to the web content, for example by providing their own data. In the present times, especially young people increasingly interact with self-monitoring technology (Millington, 2009). During digital self-tracking, a person's subjective and analogue habits, moods, thoughts, etc. are transformed into objects or digits to be scrutinized (Albrechtslund, 2013). During the transformation process, potential risks of incorrect data transformation are possible. In contrast to traditional self-tracking practices, digital media provide a quantification of subjective states that imply objectiveness and appear to be true and trustworthy. Furthermore, digital devices deliver feedback, helping users to understand and potentially modify their behavior (Crawford et al., 2015). Also, tracking behavior via tracking tools was found to be more consistent and less fragmented and sporadic compared to tracking behavior without a tracking tool in patients (Patel et al., 2012). Self-tracking via digital media can be conducted via computer programs (e.g., spreadsheets), via smartphone applications, and wearable devices that have been introduced in Chapter 2.

4.2.1 Tracking apps. To the present, a variety of smartphone applications exist that are designed to track specific aspects of life, ranging from sleep patterns to blood glucose levels or sexual activity (Figure 39).

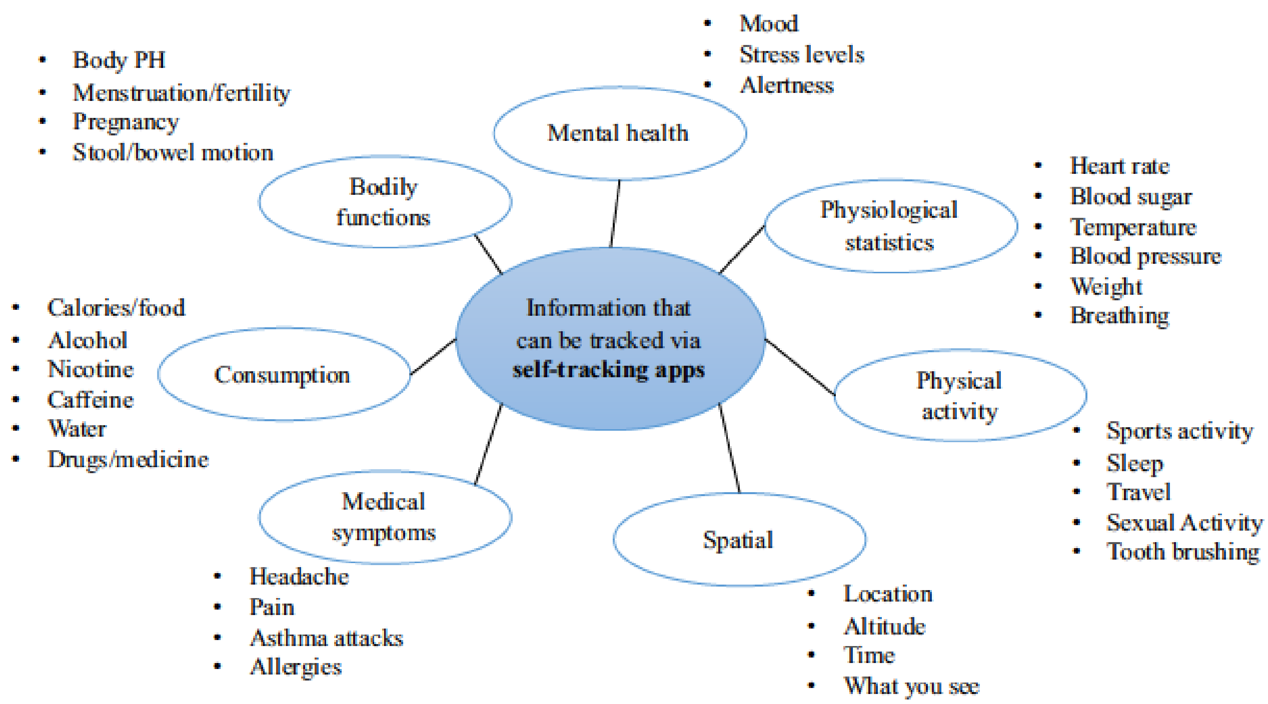


Figure 39. Information that can be assessed and processed via self-tracking apps, adapted from Barcena et al. (2014).

The most prominent apps on the field of tracking apps are fitness apps (Barcena et al., 2014) that have been designed to combat physical activity dropout rates, especially in young people (Lupton, 2013). Fitness apps and their functions (including tracking and other functions), and the related benefits and risks have been described in Chapter 2 in detail.

4.2.2 Tracking wearables. As indicated, a variety of tracking wearables exist, including small accelerometer applications, wristbands, and belt sensors that have been used even before fitness apps emerged (Zheng et al., 2014). As reviewed by Shull et al. (2014), wearable devices have been applied in healthcare to identify, evaluate, and modify movements based on touch, audio, or visual feedback. Out of the total of 92 reviewed studies, the majority of research has been conducted using goniometers (i.e., measuring the ankle of a joint), accelerometers (i.e., measuring the acceleration or speed of a movement), or gyroscopes (i.e., measuring the rotation and change of directions).

In medical healthcare, wearable devices can be beneficial to evaluate and treat diverse diseases, such as osteoarthritis, vestibular loss, Parkinson's disease, or hemiplegia (Shull et al., 2014). On the one hand, wearables use *sensing* technology that can be attached to the trunk, the knee, the shank, or the hip. For example, wearable systems have been found to be helpful in assessing foot joint angles during gait in the treatment of osteoarthritis (Rouhani, Favre, Crevoisier, & Aminian, 2012). Motoi et al. (2007) found that wearable sensor systems can be beneficial in monitoring posture changes in persons diagnosed with hemiplegia. Similarly, motion sensors applied to the body can detect balance and gait deficits in persons diagnosed with multiple sclerosis (Spain et al., 2012).

On the other hand, wearable devices can also provide *haptic feedback*. Using the feedback of wearable devices, Wall, Wrisley, and Statler (2009) found that vibrotactile tilt feedback can improve gait patterns (i.e., dynamic gait). Vibrotactile biofeedback has also been used to train trunk sway in Parkinson's disease (Nanhoe-Mahabier, Allum, Pasman, Overeem, & Bloem, 2012). Also, training of multi-parameter gaits was found to improve knee adduction via haptic feedback (Shull, Lurie, Cutkosky, & Besier, 2011).

In sport and exercise sciences, wearables have been used to improve training outcomes. Kidman, D'Souza, and Singh (2016) found that wearable devices with motion tracking and vibro-tactile feedback helped competitive divers and their coaches to identify failure modes. Therefore, training outcomes could be improved, resulting in higher quality of the athletes' dives. Ahmadi, Rowlands, and James (2009) indicated that the application of a wearable device can improve the skill assessment and skill acquisition during the first serve in tennis players. Wearable devices have been used to quantify the frequency and impact of high intensity tackles in professional Australian football players (Gastin, McLean, Spittle, &

Breed, 2013). Also, GPS tracking devices can be helpful tools to analyze training outcomes in athletes in detail. Consequently, more precise decision making during the training process are possible and can assist to improve training outcomes (Malone, Lovell, Varley, & Coutts, 2017).

Tracking one's own physiological parameters has been found to be related to a higher correspondence of perceived stress and objective measures of heart rate (Van Dijk, Westerink, Beute, & Ijsselsteijn, 2015). Similarly, the real-time feedback provided via wearable devices has been identified as a form of biofeedback (Bechly, Carender, Myles, & Sienko, 2013; Horak, Dozza, Peterka, Chiari, & Wall, 2009; Nanhoe-Mahabier et al., 2012). Biofeedback is a method using objective feedback via measurement that helps to create awareness of body functions, including heart rate, joint angles, or bowel movement (Schwartz & Andrasik, 2017). Therefore, biofeedback can be helpful to identify disordered functions and behavior and to establish healthier or more adaptive behavior. Biofeedback has been successfully applied in multiple contexts, including the treatment of stress management, anxiety disorders, and even in therapy of chronic constipation (Benninga, Büller, & Taminiau, 1993; Lemaire, Wallace, Lewin, de Grood, & Schaefer, 2011; Rice & Ashby, 2007). The use of wearables can also be helpful to evaluate outcomes of interventions, such as surgery (Shull et al., 2014).

Overall, the use of digital media provides a benefit in self-tracking practices compared to analogue and subjective practices. In medical treatment and health promotion (e.g., physical activity, calorie consumption, movement disorders), health apps and wearables have been shown to be efficient in both providing information for evaluation and treatment (e.g., via motion feedback). However, self-tracking in general, via smartphone applications or wearables can also entail certain risks.

4.2.3 Risks of self-tracking. The risks of self-tracking can be rooted in aspects that are related to the data collection, storage, transfer, and associated privacy concerns that are specific to digital devices and have been described in Chapter 2 in detail. Especially systems that store and process the data at multiple spots (e.g., on the smartphone, in the wearable, with the app provider, on external clouds/servers, etc.) are vulnerable to misfunction, misuse, and data theft (En & Pöll, 2016). This becomes especially dangerous when the users are not aware that their activity is being tracked and analyzed (Barcena et al., 2014; Crawford et al., 2015). The issues of self-tracking via all sorts of media and devices potentially lead to identity theft, profiling, location of users or stalking, corporate use and misuse, and extortion or embarrassment (details see Chapter 2). With regards to corporate use, potential conflicts of interest within the healthcare industry exist, including pharmaceutical interests to sell products, or interests of health insurance companies to gather highly personal data about their customers (Krieger, 2013).

Moreover, risks associated with general self-tracking can also be rooted in psychological aspects. With regards to these psychological risks, it has been indicated that fitness apps can promote an ideal body that is unattainable for most users (Depper & Howe, 2017). Self-tracking can increase the visibility of health, which can be perceived as a burden and create anxiety in users (Lupton, 2013). Also, group specific risks associated with fitness app usage can emerge, for example when using calorie tracking functions. Calorie tracking including tracking of intake and consumption via lists, diaries, or smartphone applications have consistently been found as influencing factors to be on a trajectory towards eating disorders (e.g., Jacobi, Paul, & Thiel, 2004). Therefore, self-tracking in terms of calorie tracking via fitness apps has been connected with eating disorders, as outlined in Chapter 2.

Besides its applications in clinical healthcare or athlete training, tracking devices have become popular in the broad population and have contributed to the formation of a lifestyle—the quantified self.

4.3 The Quantified Self

A lifestyle associated with collecting and tracking body-related data has been described as the *quantified self* (Nafus & Sherman, 2014; Wolf, 2009). The quantified self was established by Gary Wolf and Kevin Kelly on their quantified self-website in 2007 (Quantified Self Labs, 2015). The website was designated by the slogan "self-knowledge through numbers". The quantified self-movement offers a forum for self-trackers, sharing their experiences and ideas via the internet or via personal contact. In communities across the U.S., local groups exist to share their experience with their practice of self-tracking (Nafus & Sherman, 2014). Since 2011, the practice of self-tracking has also become subject to scientific research and has been predominantly based on ethnographic observation and structured interviews. The results and implications have been discussed in regular workshops (e.g., "data hack nights") or the annual Quantified Self Conferences (Nafus & Sherman, 2014).

Within the quantified self-movement, the practice of self-tracking has been described as creating a mirror of the self. Self-tracking allows people to reflect on themselves and gain insight, producing self-awareness and self-knowledge about one's body (Wolf, 2010). Therefore, a person can learn about states and processes inside of their body by means of digital self-tracking and specific feedback. For example, it has been indicated that self-tracking can support habit formation (Nafus & Sherman, 2014). Monitoring their sleep can make persons become aware of their sleep duration and quality, and can also help to shape sleeping routines (e.g., going to bed earlier, establishing mechanisms to remind for bed time). The experience of self-tracking was described as gaining "a fuller experience of what changes in date, such as rising glucose levels, might physically feel like. One learns how to feel one's body through the data" (Nafus & Sherman, 2014, p. 1789). Similarly, Sharon and Zandbergen (2017) described monitoring body-related parameters via technical devices as a way to practice mindfulness and recalibration of body sensations. In theirs study, one participant described tracking himself would allow him to "develop a 'skill', even a 'sixth sense'", learning to improve his estimate of the number of calories in a serving of food (Sharon & Zandbergen, 2017; p. 1700). Self-tracking was also described as a matter of trusting and calibrating subjective body sensations with objective data provided by the app. For example, this process was described as a matter of trusting by one participant:

> 'what do I trust?' […]: I am starting to say, "now what I feel aligns with my objective data and I trust my objective data and I trust my objective data more' or you say 'I trust my subjective data more, my subjective feeling, intuition more, and I can now process that data in a way that aligns with the subjective feeling.' (Sharon & Zandbergen, 2017; p. 1700).

Overall, constant self-monitoring via technical devices (i.e., fitness apps) has been described as a way of listening to body states and practicing body awareness (Sharon & Zandbergen, 2017). In this context, fitness apps provide the possibility to control, and therefore bridge the gap to trusting. However, it has not been investigated whether fitness app usage can contribute to higher levels of trusting.

Thus, beyond the background of body related risks that are associated with self-tracking, the matter of trust arises. The aspect of body trusting has yet scarcely been targeted in previous research, and it is unclear whether body trusting can be regarded as an aspect of trust. Nevertheless, body trusting has been targeted in the context of more general body awareness. Therefore, when examining the implications of self-tracking via fitness apps, it is crucial to identify a theoretical model that integrates aspects of general body awareness, and more specifically, body trusting.

4.4 Integrative Model of Body Awareness

Body awareness is a multi-faceted concept that is used across different fields, including psychology, medicine, and sport and exercise sciences (e.g., Crescentini & Capurso, 2015; Gyllensten, Skär, Miller, & Gard, 2010; Tihanyi, Böör, Emanuelsen, & Köteles, 2016).

The current research on body awareness related aspects is founded on diverse definitions and conceptualizations. In addition, these terms (e.g., mindfulness, somatic awareness, proprioceptive awareness, body awareness) vary in their conceptual complexity, sometimes covering small aspects and sometimes covering broad classes of body awareness. Beyond this background, Mehling et al. (2009) conducted a systematic review, describing and categorizing aspects of body awareness.

In a first step, body awareness and contextually comparable constructs were defined, and differences to other conceptualizations were outlined. In general, body awareness is defined as the "perception of bodily states, processes and actions that is presumed to originate from sensory proprioceptive and interoceptive afferents and that an individual has the capacity to be aware of" (Mehling et al., 2009, p. 4). Body awareness, somatic awareness, or interoceptive awareness are regarded as relatively synonymous across research and are described as a class of processes including perception, evaluation, regulation, and related behavior on the basis of bodily sensations. In comparison with body awareness, other similar but somewhat distinct constructs exist. For example, mindfulness is a narrower concept that mainly describes the non-judgmental acceptance of body sensations and the experience of one's body in the present moment (Carruthers, 2008). Proprioceptive awareness is another narrower concept that explicitly refers to conscious perception of objectively measurable muscle tension, angles of joints, heart rate, etc. (Laskowski, Newcomer-Aney, & Smith, 2000). After this first step of conceptualizing body awareness, an integrative questionnaire measuring body awareness was established.

Thereof, items were refined from the reviewed questionnaires to establish an item pool covering all identified aspects of body awareness (Mehling et al., 2012). After conducting cluster analyses and confirmatory factor analyses (CFAs), eight interrelated scales were identified (Figure 40): (1) noticing: awareness of neutral, pleasant, and unpleasant body sensations; (2) not distracting: ignore uncomfortable sensations or distract oneself from these; (3) not worrying: not experiencing emotional distress when feeling discomfort or pain; (4) attention regulation: capability to control and maintain attention to body sensations; (5) emotional awareness: consciousness of the association between emotional states and body sensations; (6) self-regulation: ability to regulate psychological distress by attention to body sensations; (7) body listening: active listening to body sensations to gain information about body states; (8) body trusting: experiencing the body as safe and trustworthy (sample items see Table 5).

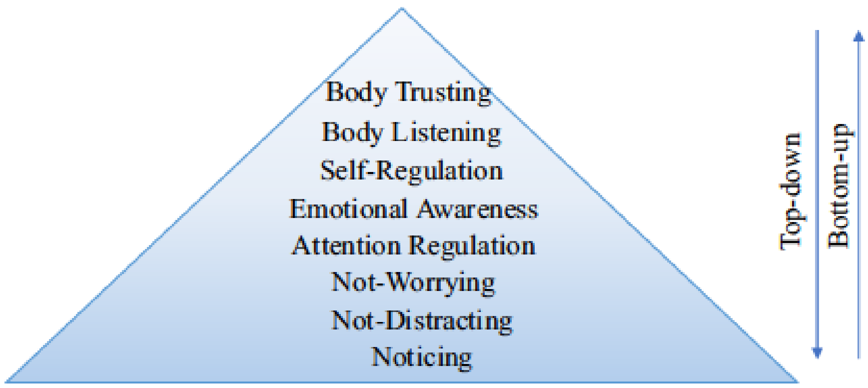


Figure 40. Visualization of the scales included in the questionnaire, including top-down and bottom-up processes, adapted from Mehling et al. (2012).

From theoretical perspective, the eight scales are assumed to describe a hierarchical process including efferent (bottom up) and afferent (top down) mechanisms: A person would first become aware of their body sensation, then experiences an attentional response (i.e., distracting or paying attention), and potentially experiences an emotional reaction. The person would then regulate the attention and would be aware of a so-called mind-body integration (i.e., being aware of the connection between emotions and body sensations). Finally, a person would (or would not) trust his or her body and react with a corresponding behavior.

Table 5

Scales of Body Awareness

Relation between scales	**Scale**	**Number of Items**	**Sample Item**
Bottom-up Top-down	(1) Noticing	4 items	*I notice in where in my body I am comfortable.*
	(2) Not Distracting	3 items	*I distract myself from sensations of discomfort.*
	(3) Not Worrying	3 items	*When I feel physical pain, I become upset.* (inversed)
	(4) Attention Regulation	7 items	*I can pay attention to my breath without being distracted by things happening around me.*
	(5) Emotional Awareness	5 items	*I notice how my body changes when I am angry.*
	(6) Self-Regulation	4 items	*I can use my breath to reduce tension.*
	(7) Body Listening	3 items	*I listen to my body to inform me about what to do.*
	(8) Body Trusting	3 items	*I trust my body sensations.*

To examine the theoretical model on a statistical level, (1) a one-factor-model (representing one overall factor of body awareness instead of eight dimensions), (2) a hierarchical model (as described above), and (3) an eight-factor model with individual scales were compared. A CFA indicated a non-sufficient model fit for the one-factor model. Compared to the hierarchical model demonstrating good validity, the eight-factor model displayed a slightly better model fit. Therefore, individual factors with a potentially weak hierarchical connection were assumed. The resulting questionnaire including a total of 32 items was named the *Multidimensional Assessment of Interoceptive Awareness* (MAIA) (Mehling et al., 2012). In a consecutive study targeting external validation, the MAIA was compared with anxiety scales. Furthermore, MAIA scores were compared between students/little experienced persons vs. experienced teachers in the field of therapies including body awareness components (i.e., meditation, yoga, mindfulness, breath therapy, etc.) Teachers reported higher levels of noticing, not-worrying, attention regulation, self-regulation, and body listening compared to the students.

The MAIA questionnaire was translated to the German language by Bornemann, Herbert, Mehling, and Singer (2015). The questionnaire was tested via a CFA, demonstrating good reliability and validity. In their study, a training program including interoception and meditation practice was implemented. After the three-month intervention, measures of body listening and trusting had increased compared to a re-test control group. The results indicate that a training program including interocpetion can enhance the capability to regulate and listen to internal states, to perceive body and mind as a whole, and to trust the body (i.e., feel home in the own body). In contrast, measures based on more basic levels, such as noticing and the quality of attention (distracting, worrying, etc.) had not changed after the intervention. The results of the study imply that regulatory and trust related aspects of body awareness are sensitive to interventions targeting interoception and can be potentially modified.

Overall, the described tool provides a self-report of perceiving, evaluating, regulating, and reacting on the basis of body sensations (Mehling, 2009). Therefore, a measure of *subjective* body awareness was provided. In contrast, *objective* measures, such as bio-feedback, have been used to examine the detection and discrimination of selected body related parameters (i.e., heart rate, muscle tension; Frank, Khorshid, Kiffer, Moravec, & McKee, 2010; Lehrer et al., 2003). Thus, objective measures can be a useful tool to measure proprioceptive awareness, i.e., the pure perception of movements, muscle tension, posture, etc. (Laskowski et al., 2000). However, proprioceptive awareness represents a singular element of body awareness that is not sensitive to body awareness changing interventions (Khalsa, Rudrauf, Sandesara, Olshansky, & Tranel, 2009; Khalsa et al., 2008).

Across scholars, high levels of body awareness are considered to be beneficial: Body awareness has been associated with higher ability to register body sensations (Hebert, 2016), and has been associated with psychological well-being (Brani, Hefferon, Lomas, & ldots, 2014; Köteles, Kollsete, & Kollsete, 2016). Furthermore, high levels of body listening and trusting have been associated with higher regulatory body-related abilities and are assumed to facilitate the management of diseases such as chronic back pain (Mehling et al., 2009). After a three months training program that targeted interoceptive awareness via meditation practice, measures of attention regulation, emotional awareness, self-regulation, body listening, and trusting increased compared to a re-test control group (Bornemann et al., 2015).

In the field of sport and exercise sciences, body awareness has been found to be higher in athletes compared to non-athletes (Minev, Petkova, Petrova, & Strebkova, 2017), and higher in advanced yoga and Pilates practitioners compared to beginners (Tihanyi, Sági, Csala, Tolnai, & Köteles, 2016). Alentorn-Geli et al. (2009) identified body awareness as a training component that can reduce risk factors of physical injury in sports. Body knowledge (similarly defined as body awareness) can also lead to higher body trust and modify the exercise process based on body sensations (Parviainen & Aromaa, 2017). In a relaxation intervention that targeted body awareness in taekwondo athletes, positive effects on the athletes' performance were found (Ottoboni, Giusti, Gatta, Symes, & Tessari, 2013).

In sum, body awareness has been identified as a multi-faceted construct describing a class of processes including perception, evaluation, regulation, and behavior on the basis of bodily sensations. One of these aspects is body trusting, representing an evaluation of the body, explicitly as trustworthy.

4.5 Body Trusting

Body trusting is defined as experiencing the body as safe and trustworthy (Mehling et al., 2012). The scale includes the three items *"I am at home in my body."*, *"I feel my body is a safe place."*, and *"I trust my body sensations."*. During a literature review yielding the establishment of the MAIA questionnaire, ten questionnaires were regarded eligible for providing adequate items measuring aspects of body awareness. Out of the ten questionnaires, four questionnaires included items that were categorized as body trusting and that were included in the preliminary item pool: (1) Styles in the Perception of Affect Scale (SIPOAS; Bernet, 1996), one item used; (2) Body Sensation Interpretation Questionnaire (BSIQ; Clark et al., 1997), eight items used; (3) Eating Disorder Inventory (EDI-C; Garner, 1991), two items used; (4) Perception of Bodily Sensations Questionnaire (PBSQ; Schneider, Löwe, & Streitberger, 2005) one item used. In sum, the concept of body trusting has been approached from diverse perspectives including clinical psychology (e.g., EDI-C, BSIQ), medicine (PBSQ), and personality psychology (i.e., emotional intelligence; SIPOAS) perspective. However, body trusting has neither been examined from traditional trust research perspective, nor has it been connected with such theories. Beyond the background of multiple body related risks associated with fitness app usage and potential control mechanisms to bridge these risks, it is crucial to understand the role of body trusting in the context of fitness app usage. Furthermore, it is yet unclear whether body trusting can be regarded as a novel form of trust.

Overall, this Chapter 4 provided insight into fitness app usage as a form of practicing self-tracking, which has become popular within the quantified self-movement. Self-tracking via fitness apps has been described as a means to practice body trusting in previous works. Therefore, the establishment of a theoretical framework of body awareness was presented that entails the aspect of body trusting. In the next Chapter 5, the areas of communication technology, trust, risks and benefits, and aspects of body and health that have been presented throughout the Chapters 1-4 are connected. Beyond the background of the heuristic research framework model introduced in this work, specific research questions are developed.

5. Research Program

Technologies and technology usage have become important and beneficial in everyday life and in professional contexts (Agarwal & Prasad, 1998; Bassellier et al., 2001). Technology usage not only provides benefits to the user, but non-usage can even involve risks: If a person refuses to use a technology in professional context, this might endanger a company's competitive survival (Agarwal & Prasad, 1998). Thus, it has become of interest to examine the acceptance and adoption of technology. Specifically, smartphone usage has been widely adopted and has created the opportunity for large frequency interaction (Statista, 2018). Therefore, health practitioners have become interested in implementing health behavior related options and gadgets (Riley et al., 2007; West et al., 2012). Over the past decades, overweight and obesity have increased, raising the need to implement low-cost and low-threshold options targeting overweight in the broad society. Fitness apps have been designed to implement health related behavior in the field of physical activity, and are promising tools to enhance health behavior and physical activity (Schoeppe et al., 2016; West et al., 2012). Meanwhile, large parts of smartphone users regularly track health related parameters to gain insight into their bodies—for health treatment purposes or just for fun (e.g. Barcena et al., 2014).

Introducing the main fields of study targeted in this work—communication technology usage, aspects of body and health, and risks and benefits (i.e., raising the matter of trust)—a research framework model was developed that provides a guideline throughout the research conducted in this work (Figure 41). Beyond the background of these three fields, areas of overlap were identified, i.e., *fitness app usage*, *trust in technology*, and *trust in the body*. Therefore, it is an overarching aim of this study to understand the associations and interrelations between these three fields to provide practice-relevant implications for healthy fitness app usage, and implications for theory building in the interdisciplinary fields of trust research, technology usage, and health and exercise sciences. Specifically, it is an aim to shed light onto the processes of initiation of, maintenance of, and dropout from fitness app usage beyond the background of trust research, and to extend models of traditional trust research by integrating aspects of risk and benefit. Furthermore, it is an aim to identify the role of trust in body trusting, and to examine the risks and benefits of fitness app usage with regards to health and trust related aspects. The specific research questions derived from this framework model are outlined in the following. To address these research questions, three studies, in particular Study A, Study B, and Study C were designed that look at these topics from diverse perspectives and via different analyses. The three studies each target one, two, or all three relations between the three intersections of trust in technology, body trusting, and fitness app usage.

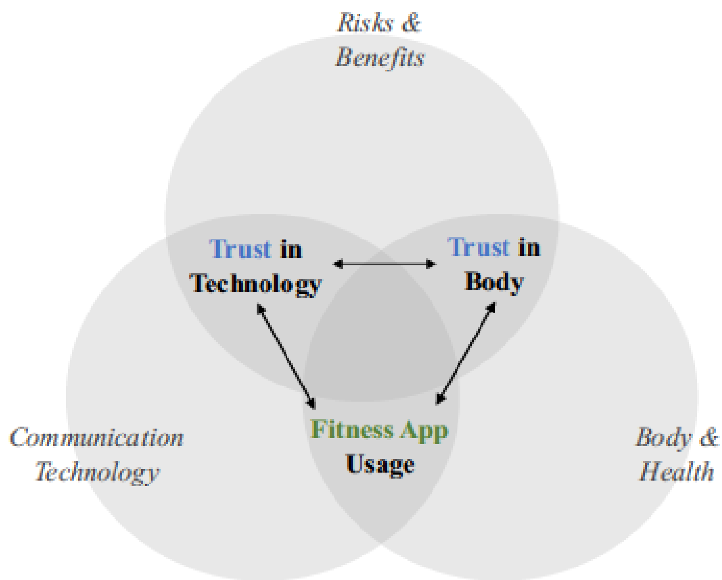


Figure 41. Proposed research framework model to identify the interrelations between fitness app usage, trust in technology, and body trusting beyond the background of risks and benefits. *Note:* Trust variables are marked *blue* and fitness app related variables are marked *green* throughout this work to provide a better overview.

5.1 Study A: Fitness App Usage and Trust

5.1.1 Fitness app usage. Fitness apps represent a promising low-cost and easily applicable opportunity to support initiation and maintenance of physical activity (Schoeppe et al., 2016). However, fitness app usage is associated with high dropout rates (GfK, 2017). Facing these high levels of dropout, the investigation of factors associated with initiation of and dropout from fitness app usage is of high societal interest in order to establish positive effects in everyday life (Reinwand et al., 2015). Accepting potential risks associated with fitness app usage (e.g., data insecurity, low reliability of data), trust might be a key element in the users' decisions about initiation of, duration of, and dropout from fitness app usage. Thus, the concept of trust in the specific technology might be a substantial factor explaining the initiation of and dropout from fitness app usage. With regards to other psychological variables such as motivation and personality, fitness app usage has been connected with intrinsic forms of motivation and long-term goal attainment (Clinger, 2015; Rönkkö, 2018). Also, high levels of neuroticism were found to predict calorie tracking in fitness app users (Embacher et al., 2018). With regards to other personality related variables, excessive extents of general smartphone app usage have been associated with narcissism (Hussain, Griffiths, & Sheffield, 2017). Thus, it can be assumed that intrinsic forms of motivation (including goal achievement and needs satisfaction), and neuroticism and narcissism can be associated with fitness app usage.

To gain a general and broad understanding of aspects and variables associated with fitness app usage (i.e., initiation, maintenance, and dropout), it was a first aim to identify psychological and exercise related variables that are associated with fitness app usage and dropout. Therefore, Study A was designed as a comprehensive questionnaire assessing a broad range of variables in the fields of personality, motivation, and specific assumptions about the fitness app (i.e., trust in the fitness app), and to connect these with the duration and frequency of fitness app usage. Furthermore, it was an aim to explore factors associated with dropout from fitness app usage in an open and exploratory format. In sum, it can be assumed that trust in technology is an important influencing factor in the context of fitness app usage.

5.1.2 Trust in technology and fitness app usage. As forms and environments of communication and trust change, so do new forms of trust and risk emerge. According to general definitions of trust, trust is the willingness to be vulnerable under risky conditions (Mayer et al., 1995), and is considered crucial in any situation that is associated with risks or uncertainty (Luhmann, 1979; Schoorman et al., 2015). Therefore, it is argued that the concept of trust can be applied to communication contexts beyond interpersonal relations, i.e., in communication with technology or IT artefacts (Lee & See, 2004; McKnight et al., 2011; Söllner et al., 2012).

Traditional interpersonal and analogue communication shift to communication via digital media (e.g., social networks), and also to communication with the media, such as computer programs or the smartphone. Consequently, the technology can hold the role of the *trusted object,* or the trustee (Söllner et al., 2012). McKnight et al. (2011) postulated that trust is an important influencing factor in the technology usage as persons rely on technologies while facing various risks. Therefore, the need was raised to establish an application of the traditional interpersonal concept of trust to the context of a digitized world. Traditional concepts of interpersonal trust focusing face-to-face interactions (e.g., Mayer et al., 1995) needed to be adapted to the digital and non-face-to-face, and from the personal to the impersonal context.

Therefore, McKnight et al. (2011) established a comprehensive model to explain post-adaptive usage of a specific technology from a psychological perspective. By laying focus on trusting beliefs in the technology itself, it was assumed to gain a more precise understanding of what makes a technology trustworthy, instead of persons or contexts associated with such usage (McKnight et al., 2011). The trust in a specific technology model is rooted in previous work on conceptualizations of interpersonal trust and distrust as well as in trust in e-commerce contexts (Mayer et al., 1995; McKnight & Chervany, 2001; McKnight et al., 2002). The trust in a specific technology model was established and tested in the field of specific computer programs, explicitly referring to a spreadsheet program (Excel). However, the model has yet to be applied to newer, wearable technologies, such as fitness apps.

McKnight et al. (2011) implied the necessity to differentiate between different stages of usage when investigating trust in technology (e.g., non-usage, usage, and post-usage/dropout). First, *propensity to trust* and *institution-based trust* represent non-specific assumptions that can be observed and relevant during initiation of usage. Second, *trusting beliefs* can be important to explain the maintenance of usage and dropout from usage. In doing so, comprehensive and precise analysis of the initiation of, maintenance of, and dropout from fitness app usage is possible. Therefore, Study A was designed to test the model of trust in a specific technology (McKnight et al., 2011) in the field of fitness apps, shading light onto the processes of initiation and dropout by analyzing a sample of non-users, users, and dropout (Figure 42). In sum, it can be assumed that the trust in technology model (McKnight et al., 2011) can be applied to the fitness app context and can explain the initiation of, maintenance of, and dropout from fitness app usage.

Figure 42. Visualization of the specific research question based on the model of trust in technology (McKnight et al., 2011) and the relations between the variables tested in Study A.

5.1.3 Aspects of trust, fitness app usage, and exercise. Beyond the background of multiple risks that are associated with fitness app usage, trust (and specifically trust in technology) has been assumed to be a key element explaining fitness app usage (e.g., Barcena et al., 2014; McKnight et al., 2011). At the same time, fitness apps have been designed to enhance physical activity, such as exercise (West et al., 2012). Therefore, when aiming at understanding and explaining fitness app usage, the effects on fitness app usage, but also on exercise behavior are of high interest. Fitness app usage can entail *technology related* risks, such as issues with privacy and data security (e.g., Barcena et al., 2014; Crawford et al., 2015). At the same time, fitness apps provide *body related* feedback and prompts that guide health related and exercise related behavior. Potential risks of usage can be associated with unreliable measurements, flaws in calculation and instructions regarding exercise, movements, or nutrition (e.g., Kaewkannate & Kim, 2016). These might lead to health risks such as wrong or unbalanced body movements, unhealthy nutrition, and inappropriate exercise behavior. Therefore, it can be assumed that not only trust in technology, but also body related trust can be of relevance to understand the processes associated with initiation and dropout from fitness app usage.

In sum, two aspects of trust are of relevance in the context of (A) fitness app usage and (B) exercise: trust in technology, i.e. the fitness app; and body trusting (Figure 43).

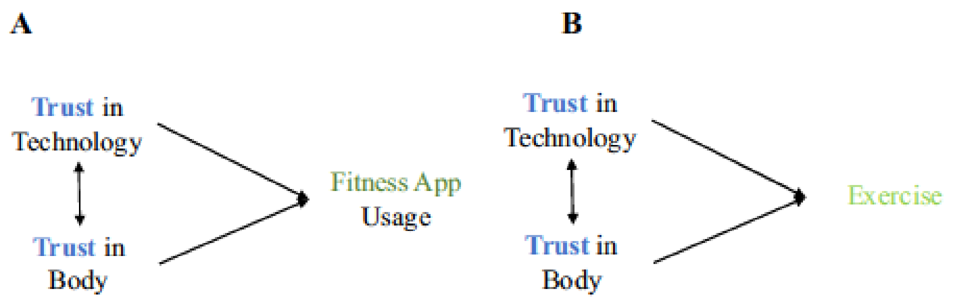


Figure 43. Visualization of the specific research question and the relations between the variables tested in Study A targeting the influence of trust in technology and body trusting on (A) fitness app usage and (B) exercise behavior.

Trust in technology has been identified as a predictor of fitness app usage, but trust in fitness apps has not been connected with exercise behavior yet. Body trusting is a novel and relatively unexamined construct evolving from research on body awareness (e.g., Mehling et al., 2012). Body trusting has neither been connected with fitness app usage nor has it been considered in the context of trust research or beyond the background of trust models in previous research. Moreover, no study has focused on the relationship between body trusting and exercise behavior so far.

Therefore, it was another aim to examine body trusting in the context of trust research. Furthermore, it is of interest to understand the interrelations between body trusting and trust in technology, and to understand how they interact to explain fitness app usage and exercise behavior. In doing so, data collected in Study A was used to explore and identify the relations between body trusting, trust in technology, and to explore under which circumstances their interaction influences fitness app usage and exercise behavior. In sum, it can be assumed that trust in technology and body trusting are interrelated as they both reflect trust related concepts. Furthermore, it can be assumed that trust in technology and body trusting can be connected with fitness app usage, and that body trusting can be connected with exercise.

5.2 Study B: Trust, Risk, and Benefit

It has been demonstrated that fitness app usage is associated with a range of *benefits*, such as providing feedback about body related processes, or promoting health behavior. For example, fitness apps can be useful tools to establish exercise routines and to enhance physical activity such as the daily step count (e.g., Schoeppe et al., 2016, West et al., 2012).

At the same time, fitness app usage can entail certain *risks*. During fitness app usage, highly private and vulnerable data such as health status, mood, or even sexual activity are collected, analyzed, and stored. Therefore, potential risks can relate to privacy concerns and potential data misuse (e.g., Barcena et al., 2014). Systematic biases in data tracking and estimation can pose risks to the users' health (e.g., Kaewkannate & Kim, 2016). Moreover, specific user groups such as persons disposed to eating disorders can be prone to psychological risks with regards to the tracking function of fitness apps (e.g., Simpson & Mazzeo, 2017). In sum, digitalization and fitness app usage entail both risks and benefits that might guide the initiation of, maintenance of, and dropout from fitness app usage.

Specifically, people make themselves vulnerable and provide their personal data to data processing (e.g., external servers) they have little knowledge about. At the same time, progress in media and digital communication changes rapidly, providing small starting points of experience and knowledge (e.g., Rosa & Scheuermann, 2010). Hence, the person-app relation is based on little knowledge and experience. Especially when the perceived trustworthiness of a trustee is based on little or no personal experience at early stages of trustor-trustee relationships—such as during rapid changes in media progress—initial trust is present (Lewicki & Bunker, 1996; McKnight et al., 2011). The formation of initial trusting intentions and behavior are mainly guided by the assessment of costs/risks and benefits (Lewicki & Bunker, 1996). In contrast to experience-based evaluations, benefit and risk assessments are dominant in this evaluation of trustworthiness. Therefore, when examining initial trust in digital environments, risk vs. benefit assessments are crucial factors to consider and can be of predictive value. For example, this has been demonstrated in research on the influence of initial trust in web vendors on online purchase intentions (Gefen et al., 2003; Vance et al., 2008). Also, risk vs. benefit assessments and behavioral intentions are central elements of the Technology Acceptance Model (TAM, Davis et al., 1989), and are represented by the perceived usefulness (i.e., the benefit) and the perceived ease of usage. The TAM has successfully been applied to explaining consumer intentions and decisions (Gefen & Straub, 2000; Szajna, 1996; Taylor & Todd, 1995).

Previous research targeting the elaborate explanation of technology usage has gone beyond traditional trust research models, integrating both trusting beliefs and also the evaluation of risks vs. benefits. In the field of electronic commerce (e-commerce), Kim et al. (2008) identified a model based on trust research and the TAM model, explaining how trust and diverse dimensions of both perceived risk and benefit affect the intention to purchase which then leads to purchasing behavior (Figure 44). Therefore, previous research on e-commerce has indicated that the integration of perceived benefit and risk in theory building can lead to a better understanding and better explanations of intentions and behavior. In traditional models conceptualizing trust, benefit has scarcely been considered explicitly. However, the interrelations between trust, perceived risk, and perceived benefit have not yet been examined in the field of technology applications, such as fitness app usage. Therefore, Study B was designed to test the model applied by Kim et al. (2008) in the field of fitness app usage. In sum, it can be assumed that the model proposed by Kim et al. (2008) can be applied to the fitness app context.

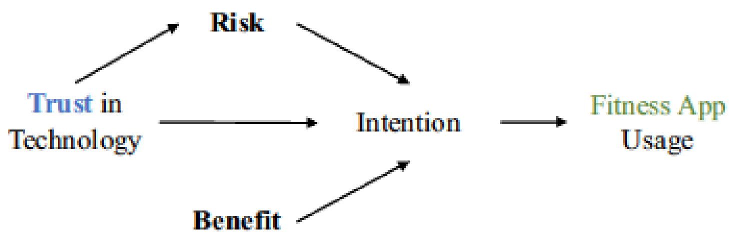


Figure 44. Visualization of the specific research question based on the model proposed by Kim et al. (2008) and the relations between the variables tested in Study B.

5.3 Study C: Longitudinal Analysis of Fitness App Usage

5.3.1 Self-tracking via fitness apps and trust. Fitness apps can be promising tools to enhance health behavior and physical activity, such as daily covered steps (Schoeppe et al., 2016). Furthermore, digital media provide a quantification of subjective states that imply objectiveness and appear to be true and trustworthy. Digital devices deliver feedback, helping users to understand and potentially modify their behavior (Crawford et al., 2015). Thus, people who are engaged in self-tracking hope to identify patterns in their behavior and find causes and trajectories of a disease or unhealthy behavior (Moschel, 2013). The implication of these issues is that human life is risky. Specifically, these risks can involve physical dysfunction, disease, and also social risks such as failing to meet social norms and standards (En & Pöll, 2016). Beyond the background of multiple risks associated with fitness app usage, trusting emerges as a key aspect. Furthermore, it has been conveyed that self-tracking is of epistemic value and can enhance well-being and quality of life (Crawford et al., 2015). One learns how to feel one's body through the data (Nafus & Sherman, 2014). Fitness apps provide the possibility to control (En & Pöll, 2014), and therefore might bridge the gap to trusting (Schoorman et al., 2015). In line with these findings, self-tracking via fitness apps has also been described as a means to practice body awareness and body trusting (van Dijk et al., 2015; Sharon & Zandbergen, 2017). However, the outcomes of fitness app usage on mental states and mental health (i.e., listening and trusting the body, psychological well-being) have yet to be focused as main research questions in empirical and experimental studies. Specifically, it is unclear how and if continuous self-monitoring of one's own physical activity level influences the effects on self-reported capability to listen to body states and how this might contribute to body trusting over time. Therefore, Study C was designed to understand the effects of self-tracking via digital media that provide objective feedback (i.e., a fitness app) on body listening, body trusting, and psychological well-being over time.

It has been indicated that trust in technology is a central aspect when explaining technology usage, such as fitness apps (McKnight et al., 2011). Also, fitness app usage has been described as a tradeoff between trusting the *subjective bodily* sensations vs. trusting the *objective* feedback provided by the *fitness app* (Sharon & Zandbergen, 2017). In connection with the potential effects of fitness app usage on body trusting described above, it can be highly relevant to consider trust in the technology when examining the effects of fitness app usage beyond the background of trust research. Specifically, it is crucial to understand whether trust in the fitness app's feedback (i.e., trust in technology) can mediate the effects of self-tracking via fitness apps on body trusting, body listening, and psychological well-being. Therefore, Study C was also designed to examine a potentially mediating role of trust in technology.

Also, the implementation of a pre-set step target is a major element in fitness app usage. However, potential effects of specific app functions (e.g., a step target of 10,000 steps per day) have yet to be examined under controlled conditions. Therefore, Schoeppe et al. (2016) concluded that it would be necessary to examine the effects of specific app functions under controlled conditions as for example examining effects of external step targets implemented in the fitness app. Specifically, it is of interest to understand the effects of specific external goal setting (i.e., 10,000 steps per day). First, such goals provided by the app might imply social norms or a reality that are unattainable for many fitness app users (Depper & Howe, 2017). This might convey a perception of social pressure instead of well-being (Lupton, 2013). Second, it is of interest to examine whether external goal setting during physical activity can shift the behavioral focus away from relying on own body perceptions to a desire to attain external cues—no matter whether it feels good or bad—and therefore undermine body listening and body trusting.

Overall, Study C was designed to examine two groups using a fitness app device under randomized controlled conditions. It was an aim to understand the process of continuous self-monitoring via fitness apps by observing potential longitudinal effects in both groups. To provide a better understanding of the general (i.e., subjective feedback) vs. fitness app specific (i.e., objective feedback) processes associated with continuous self-monitoring, it was an aim to examine an additional group that monitored their physical activity via self-report, but not via fitness apps. Also, it was an aim to systematically vary the condition by implementing a specific step target in one group (i.e., 10,000 steps per day) to understand the effect of this specific app function (Figure 45). In sum, it can be assumed that self-tracking via fitness apps can lead to higher levels of psychological well-being, body trusting, and body listening compared to a control group using no digital feedback, and that trust in technology mediates this relationship. Furthermore, it can be assumed that the implementation of an external step target (i.e., 10,000 steps per day) leads to lower levels of psychological well-being, body trusting, and body listening compared to no such implementation.

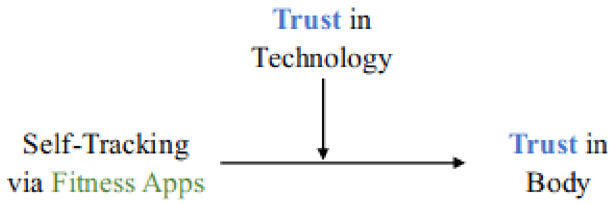


Figure 45. Visualization of the specific research question and relations between the variables tested in Study C.

5.3.2 Body trusting and well-being. In previous research, aspects of body trusting have been assessed via single items to describe interpretations of body sensations (e.g., *"I trust my body sensations"*; Mehling et al., 2012). Creating an integrative framework of body awareness, Mehling et al. (2012) first introduced the scale of body trusting as an attitude referring to the behavioral implication of bodily sensations. It reflects the extent to which a person regards body sensations as helpful information for decision making and health. However, the external validity of body trusting has yet to be examined. Therefore, it was an aim to better understand the nature of body trusting by providing external validity. Specifically, it was an aim to test the adaptiveness that has been described in the context of body trusting (Bornemann et al., 2015; Mehling et al., 2012). In doing so, the examination of connections with well-established constructs can be helpful in understanding the nature of body trusting. Therefore, variables were of interest that have consistently been connected with health in previous research, such as psychological well-being (Hoyt, Chase-Lansdale, McDade, & Adam, 2012; Neff, 2011; Ryan & Frederick, 1997). Psychological well-being represents one of the most overarching constructs that is associated with both mental and physiological health (e.g., Hoyt et al., 2012; WHO, 2017). Going beyond traditional analyses of bivariate correlations, it was also an aim to understand *causal* relations between body trusting and psychological well-being (Figure 46). To examine whether body trusting can lead to psychological well-being, data collected in Study C (see below) was used to provide external validity of body trusting, and to understand causal relations between body trusting and psychological well-being. In sum, it can be assumed that body trusting can be connected with external variables that reflect adaptiveness, and that body trusting can lead to higher levels of well-being.

Figure 46. Visualization of the specific research question and relations between the variables tested in Study C.

5.3.3 Longitudinal stability of trust in technology. Trust has been conceptualized by a range of scholars and has been studied from diverse perspectives that imply different assumptions about stability. From psychology perspective, trust is regarded as a state that lies within a person, as a mental state or attitude (Castelfranchi & Falcone, 2010), or as a state of willingness to make oneself vulnerable under risky conditions (Mayer et al. 1995) that can fluctuate over time. In contrast, Rotter (1971) defined trust as an unspecific individual trait describing the expectancy that the communication of someone can be relied on, therefore assuming high longitudinal stability. From sociology perspective, trust is not viewed as a property within a person, but rather as a quality of relationship, as a property of collective units (Sztompka, 1999).

Nevertheless, most theories imply a trait-like and unspecific component of trusting stance that is assumed to be stable over time and situations. According to the integrative model of trust, general trust propensity is regarded as a within-person attribute that is stable across situations and that refers to a person's general ability to trust (Mayer et al., 1995).

McKnight et al. (2001) differentiated between three sets of trusting beliefs varying in their degree of context and their degree of technology specificity. The three sets are the situational and technology unspecific *propensity to trust*, the context or technology specific *institution-based trust*, and the specific *trusting beliefs* in a specific technology. McKnight et al. (2011) demonstrated that propensity to trust leads to institution-based trust, which in turn leads to trusting beliefs via structural equation modelling. Although sequentiality is implied within this model, the longitudinal stability or causality within the model have yet to be tested. Therefore, it is not clear, if and how the three sets of trust in a specific technology are related with each other on a level that goes beyond cross-sectional analysis, thus, whether the concepts underlie causality. Within the integrated model of trust, propensity to trust is regarded as a trait-based perception of others that has been demonstrated to be stable across time and situations (e.g. Alarcon et al., 2016; 2018). In contrast, *institution-based trust* reflects context (i.e., technology) specific assumptions, and *trusting beliefs* reflect situation and information specific beliefs, potentially implying less stability over time and situations (McKnight et al., 2011). In previous research, propensity to trust has been shown to predict trusting beliefs in unfamiliar conditions (Alarcon et al., 2016).

Thus, to shed light upon the processes postulated within the model of trust in technology (McKnight et al., 2011), data collected in Study C was used to examine the longitudinal stability of propensity to trust, and potential causal effects within the model applied to the context of fitness app usage. In sum, it is assumed that propensity to trust is stable over time, and that a causal connection between propensity to trust, institution-based trust, and trusting beliefs exists (Figure 47).

Figure 47. Visualization of the specific research question based on the model of trust in technology (McKnight et al., 2011), and the relations between the variables tested in Study C.

Overall, a heuristic research framework model has been introduced to shed light upon the interrelations between trust in technology, body trusting, and fitness app usage. After the specific research questions had been introduced in this Chapter 5, the research framework model can be complemented by arrows indicating the relations between the variables that are examined throughout three studies, i.e., Study A, Study B, and Study C (Figure 48). An overview of the main research questions derived from this framework model including the specific samples, models and variables that are to be tested are summarized in Table 6.

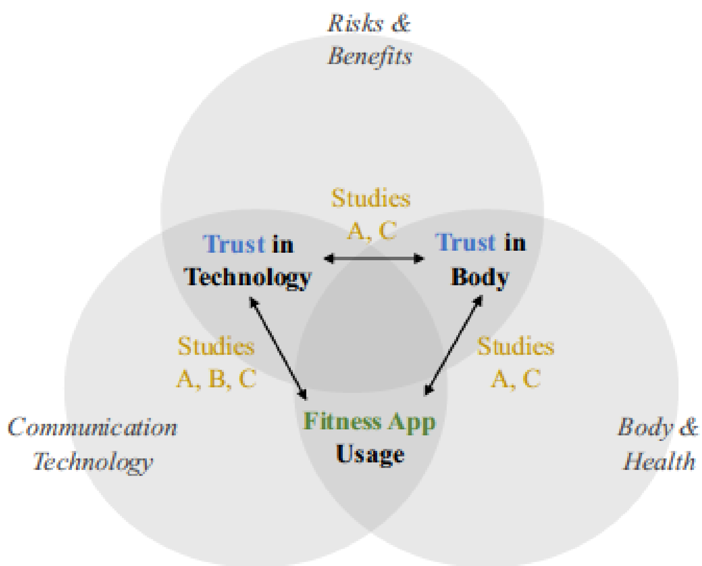
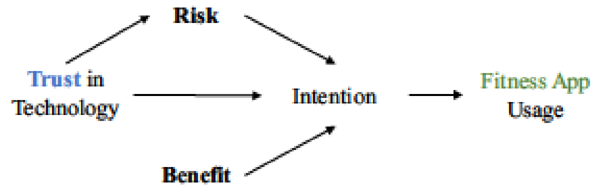
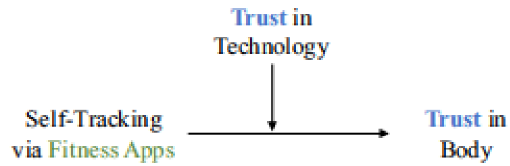


Figure 48. Overview of the three studies included in Chapter 6 to identify the interrelations between fitness app usage, trust in technology, and body trusting beyond the background of the research framework model introduced in this work.

Table 6

Overview of the Empirical Studies

Study	**Part & Sample**	**Research Question**	**Methodology**	**Visualization**
Study A	Part 1 $N = 754$	Associations between fitness app usage and a broad range of variables, exploration of factors associated with dropout	Critical Incident Technique (CIT), correlations	Fitness App Usage
	Part 2 $N_1 = 476$ *users & non-users* Part 3 $N_2 = 266$ *users & dropout*	Application of the *trust in a specific technology* model (McKnight et al., 2011) to fitness apps: Part 2 examination of propensity to trust and institution-based trust to explain initiation of usage Part 3 examination of trusting beliefs to explain maintenance of and dropout from usage	CFA/SEM & Analysis of Invariance	Trust in Technology → Fitness App Usage
	Part 3 $N_2 = 266$ *users & dropout*	Prediction of the dropout from fitness app usage	Survival Analysis	Trust in Technology → Fitness App Usage
	Part 3 $N_2 = 266$ *users & dropout*	Effects of congruence and incongruence among trust in technology and body trusting on fitness app usage and exercise	Response Surface Analysis (RSA)	Trust in Technology ↕ Trust in Body → Fitness App Usage Trust in Technology ↕ Trust in Body → Exercise

<table>
<tr><td><u>Study B</u></td><td>N = 388</td><td>Extension of the trust in a specific technology model predicting fitness app usage by considering perceived risk and perceived benefit. In doing so, a model proposed by Kim et al. (2008) was used</td><td>SEM</td><td>
</td></tr>
<tr><td><u>Study C</u></td><td><u>Part 1</u> N = 150</td><td>Effects of self-tracking via fitness apps and the implementation of an external step target on body trusting and the moderating role of trust in technology</td><td>Multilevel Bayesian Analysis</td><td>
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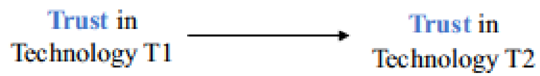
<tr><td></td><td></td><td>Examination of the external validity of body trusting and test of potential causality between body trusting and psychological well-being</td><td>Multilevel Bayesian Analysis</td><td>
</td></tr>
<tr><td></td><td><u>Part 2</u> n = 100 users & dropout</td><td>Longitudinal analysis of the trust in a specific technology model (McKnight et al., 2011)</td><td>SEM</td><td>
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Note. CFA, confirmatory factor analysis; SEM, structural equation modelling; sample sizes of N_1 and N_2 in Study A do not sum to total N in Study A due to dropout rates affecting the sample size of each questionnaire.

In sum, three empirical studies were designed to investigate the research questions in the interdisciplinary fields of psychology, communication science, and sport and exercise sciences. In doing so, it was an aim to approach the research questions via diverse and complementary methodologies including both cross-sectional and longitudinal, non-experimental and experimental designs (e.g., a randomly controlled trial; RCT), using structural equation modelling (SEM), analyses of invariance, survival analyses, response surface analyses (RSA), and multilevel Bayesian analysis. Some of the studies entail diverse parts that are partly based on the analysis of subsamples (e.g., users, non-users, and dropout), approaching to understand the processes of initiation of, maintenance of, and dropout from fitness app usage.

It was a pronounced aim of this work to provide transparency throughout all analyses of this work, and to make this research verifiable and reproducible. Therefore, comprehensive and supplementary data including the original data sets, codebooks, *R* codes of the statistical analyses, and supplementary material such as ancillary analyses are provided on the open science framework OSF https://osf.io. The data can be accessed via online links that are provided in each methods section of the studies described in Chapter 6. All three studies were approved by the ethics committee of the University of Münster prior to data collection, and the experimental Study C was registered at the German Clinical Trials Register (DRKS, 2019; details see Chapter 6). The online registration can be viewed at the WHO website http://apps.who.int/trialsearch/.

6. Empirical Studies

Study A

Fitness apps represent a promising low-cost and easily applicable opportunity to support the initiation and maintenance of physical activity (Schoeppe et al., 2016). However, fitness app usage is associated with high dropout rates (GfK, 2017). Therefore, it was a first aim of Study A to identify critical factors connected with fitness app usage and the dropout from fitness app usage, ranging from personality and motivation to trust related aspects (Part 1).

McKnight et al. (2011) postulated that trust is an important influencing factor in technology usage as persons rely on technologies while facing various risks. However, their model of trust in technology has yet to be applied to newer, wearable technologies, such as fitness apps. Therefore, it was a second aim of Study A to provide differentiated insight into the processes of initiation and maintenance of fitness app usage (Figure 49), and to test the model of trust in technology (McKnight et al., 2011; Figure 50) in the field of new technology (i.e., fitness apps in health context).

Figure 49. Visualization of the specific research question based on the model of Trust in Technology (McKnight et al., 2011) and the relations between the variables tested in Study A.

In doing so, it was the aim to investigate *propensity to trust* and *institution-based trust* in the technology of fitness apps by contrasting the groups of fitness app *users* vs. *non-users* (Part 2), and to investigate *trusting* beliefs in fitness apps by contrasting the groups of fitness app *users* vs. *dropout* (Part 3). Thus, this study is the first to apply a trust model to explain fitness app usage. Furthermore, it was the aim to gain deeper insight into the process of maintenance of and dropout from fitness app usage by investigating the survival rate and trust related predictors. Thus, this study is also the first to make process of initiation of, maintenance of, and dropout from usage visible by providing differentiated analysis across users, non-users, and dropout.

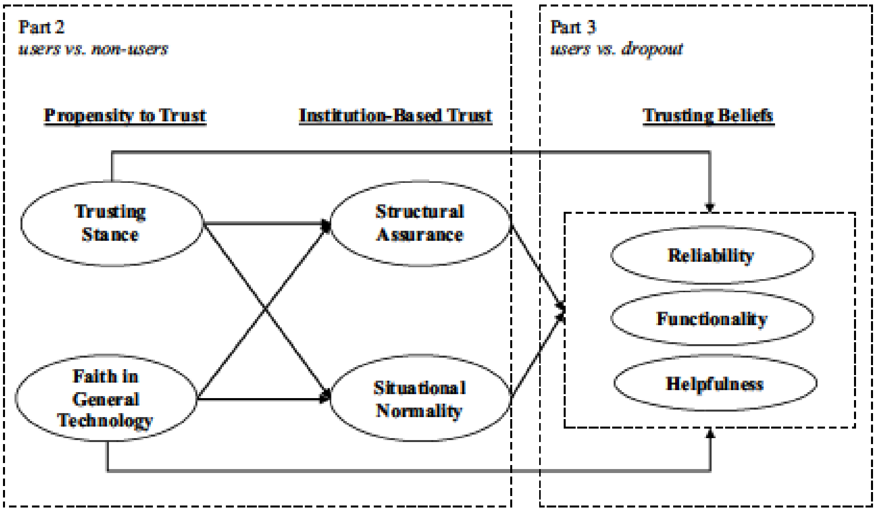


Figure 50. Visualization of the Trust in Technology model (McKnight et al., 2011) and the analyses to examine the initiation of, maintenance of, and dropout from fitness app usage.

It was another aim to examine body trusting in the context of trust research. Specifically, it was the purpose to understand the interrelations between body trusting and trust in technology, and under which circumstances their interaction influences fitness app usage and exercise behavior.

As the three parts of Study A each include different sets of samples (i.e., Part 1 including all participants, Part 2 including users and non-users, and Part 3 including users and dropout), the sample descriptions, reliability estimations, statistical analysis, etc. vary considerably. Therefore, each part is presented separately throughout Study A, followed by a general discussion of the results. In sum, Study A contributes to the understanding of relations between the three fields of trust in technology, fitness app usage, body trusting, and exercise (i.e., health) with regards to the research framework model introduced in this work[1].

[1] The development of the research design was supported by Till Utesch, Linda Schücker, and Bernd Strauss. Till Utesch provided support with the data analysis. Sydney Querfurth-Böhnlein assisted in the development of the research design and used parts of the data collected in this study for a separate analysis in her dissertation thesis.

Part 1: Fitness App Usage and Dropout: An Exploration

To gain a broader understanding of the processes and factors that are associated with fitness app usage and dropout, it was the specific aim of Part 1 to identify psychological and exercise related variables associated with fitness app usage and dropout via open and closed questionnaire formats. Therefore, Study A was designed as a comprehensive questionnaire assessing a broad range of variables from the fields of personality, motivation, and specific assumptions about the fitness app (i.e., trust in the fitness app) in order to connect these with the duration and frequency of fitness app usage. Fitness apps were mainly designed and used to enhance exercise behavior (GfK, 2017; West et al., 2012). Therefore, a relevant aspect in the examination of factors associated with fitness app usage is exercise behavior. Fitness apps also provide a large range of different app functions (i.e., exercise tracking, additional tracking of calorie intake and consumption, and other aspects related to nutrition; West et al., 2012). Therefore, it was another aim to provide differentiated analysis of the main app categories *exercise tracking* and *calorie/nutrition tracking*.

Hypotheses. In Part 1 of this study, factors associated with fitness app usage and dropout from fitness app usage are examined. Therefore, it was hypothesized:

Hypothesis 1a: Trust in technology is a relevant aspect that is associated with fitness app usage and dropout from fitness app usage.

Hypothesis 1b: With regards to personality, neuroticism and narcissism are associated with fitness app usage.

Hypothesis 1c: With regards to motivation, intrinsic forms of motivation, goal achievement, and needs satisfaction are associated with fitness app usage.

Methods

Participants and data acquisition. The data analyzed in Study A was acquired via a comprehensive online survey. Participants who were at least 18 years old were recruited via personal contact, mailing lists, and social networks, focusing on students and sport club participants. The questionnaire was provided via the online survey program *unipark* (Questback GmbH, 2018). The questionnaires were completed by a total of $N = 754$ participants (69.2% female). Skipping questions was not possible in the survey, meaning that every question had to be filled in before proceeding to the next section. The participants were $M = 30.17$ years old ($SD = 11.91$). Prior to data collection, the study was approved by the ethics committee of the University of Münster.

Fitness app usage. The participants were asked whether they (1) were currently using a fitness app (thus coded as fitness app *users*); (2) had used a fitness app in the past (coded as *dropout*); or (3) had never used a fitness app before (coded as *non-users*). $N = 248$ participants (32.89% of the total sample) were identified as *users*, n =168 participants (22.28% of the total sample) were identified as *dropout*, and $n = 338$ participants (44.82% of the total sample) were identified as *non-users*. Thus, a total of 40.38% of those participants who were experienced in fitness app usage (i.e., of the *users* and *dropout*), were classified as *dropout* from fitness app usage. If the participants had used a fitness app in the past, they were asked further questions related to the *duration* and *frequency* of fitness app usage (see below).

Duration of fitness app usage. The participants were asked for how many weeks they had used a fitness app. Seven participants were identified with extreme outliers. These measurements might have led to biased statistical analysis associated with high skewness in distribution. Thus, participants stating to have used fitness apps for > 200 weeks were excluded from the analysis. For preliminary analysis, participants were asked to state why they had stopped using fitness apps via an open question format. Here, $n = 92$ participants provided answers.

Frequency of fitness app usage. The participants were also asked to state for how many *minutes per day* and for how many *days per week* they had used fitness apps via two single items. For the statistical analysis, a new variable was calculated representing the frequency of fitness app usage in *minutes per week*. Due to statistical reasons (see above), the data of $n = 13$ participants was excluded as the participants stated to use fitness apps for > 500 minutes per week.

Exercise behavior. Based on the items of the LTEQ questionnaire (Godin & Shephard, 1997), the participants were asked to report their weekly amount of exercise in hours per week (e.g., 0.5 hours) separately for six different activities (e.g., running, swimming, biking). A composite score was calculated to analyze the total exercise behavior.

Trust in technology. To assess trust in technology, the questionnaire for trust in a specific technology (McKnight et al., 2011) was used. For this purpose, the questionnaire had been translated and back-translated to German by a native speaker, had been adapted to the fitness app context, and had been validated via a CFA (Querfurth-Böhnlein, 2018). The assessment tool includes a total of 26 items that are rated on a 7-point Likert scale ranging from 1 = *not agree* to 7 = *fully agree*. Scales measuring the aspect of propensity to trust were *trusting stance in general technology* (3 items), and *faith in general technology* (4 items). To measure institution-based trust, the scales *structural assurance* (4 items) and *situational normality* (4 items) were applied. Measuring trusting beliefs in a specific technology, the scales *reliability* (4 items), *functionality* (3 items), and *helpfulness* (4 items) were used. The original and the translated questionnaires are accessible in a supplementary file on the open science framework OSF https://osf.io/t4gfe/?view_only=61af3bab53bf4ea3837b8c4a246afbf4. To estimate reliability, Mc Donald's ω_H (McDonald, 1985, 1999) and Cronbach's α were applied. The calculation of Cronbach's α is based on the assumption of equal factor loadings, as defined in an essentially τ-equivalent model. If not meeting these assumptions, the estimation via Cronbach's α can lead to an overestimation of coefficients (Zinbarg, Revelle, Yovel, & Li, 2005). Therefore, it has been recommended to estimate reliability via Mc Donald's ω_H in case assumptions are not met (McDonald, 1985, 1999). The coefficients can be interpreted analogously to Cronbach's α coefficients (i.e., .80 indicating good reliability; Moosbrugger & Kelava, 2007). However, to facilitate interpretation and comparisons with previous studies, Cronbach's α is presented additionally. With regards to the trust in technology questionnaire, ω_H should be interpreted because a congeneric model fitted the data better than an essentially τ-equivalent model ($\Delta\chi^2[25] = 247.16$, $p < .001$). In this study, the reliability coefficients ranged from $.79 \leq \omega_H \leq .89$ ($.78 \leq \alpha \leq .89$). The item characteristics and reliability coefficients including both ω_H and α of all scales used in this study are presented in Table 7.

Body awareness and body trusting. To measure aspects of body trusting and body awareness, a German version of the Multidimensional Assessment of Interoceptive Awareness (MAIA) was used (Bornemann et al., 2015). The scale *noticing* (4 items) reflects the awareness of neutral, pleasant, and unpleasant body sensations, *body listening* (3 items) refers to active listening to body sensations to gain information about body states, and the scale *body trusting* (3 items) reflects experiencing the body as safe and trustworthy. The items were rated on a 6-point Likert scale, ranging from 1 = *never* to 6 = *always*. Reliability was $.69 \leq \omega_H \leq .81$ ($.69 \leq \alpha \leq .81$). In this study, ω_H should be interpreted as the essentially τ-equivalent model fitted the data better ($\Delta\chi^2[9] = 64.95$, $p < .001$).

Motivation. To assess diverse aspects of motivation, assessment tools based on the comprehensive and well-established Self-Determination Theory (SDT; Deci & Ryan, 2000;

Ryan & Deci, 2017) were used.

Exercise regulations are a sport specific concept derived from the SDT and the self-concordance model (Sheldon & Elliot, 1999), reflecting the concordance of a goal with personal values and interests. In this study, the German instrument for measuring the self-concordance of sport- and exercise-related goals (SKK-scale; Seelig & Fuchs, 2006) was applied. The SKK-scale consists of twelve items, measuring the scales *intrinsic*, *identified*, *introjected*, and *extrinsic* regulations (each 3 items) on a 6-point Likert scale ranging from 1 = *not agree* to 6 = *fully agree*. Validity tests indicated the instrument to be robust (Seelig & Fuchs, 2006). In this study, reliability was $.77 \leq \omega_H \leq .83$ ($.77 \leq \alpha \leq .82$). In this study, ω_H should be interpreted as the essentially τ-equivalent model fitted the data better ($\Delta\chi^2[11] = 263.38$, $p < .001$).

Exercise basic needs reflect a set of basic human needs within the SDT that every individual is desired to satisfy. To assess exercise basic needs satisfaction, the German psychological needs satisfaction in exercise scale (Rackow, Scholz, & Hornung, 2013) was used. The instrument entails eleven items. The three scales *autonomy* (3 items), *competence* (4 items), and *relatedness* (4 items) were assessed on a 7-point Likert scale ranging from 1 = *not agree* to 7 = *fully agree*. Reliability and validity have been shown to be satisfactory (Rackow et al., 2013). In this study, reliability was $.75 \leq \omega_H \leq .89$ ($75 \leq \alpha \leq .88$), and ω_H should be interpreted as the essentially τ-equivalent model fitted the data better ($\Delta\chi^2[10] = 113.20$, $p < .001$).

Exercise participation goals reflect personal goals that motivate an individual to exercise. In order to measure exercise participation goals, the Bernese motive and goal inventory in leisure and health sports (BMZI; Lehnert, Sudeck, & Conzelmann, 2011) was applied. The BMZI consists of 24 items that are rated on a 5-point Likert scale ranging from 1 = *not agree* to 5 = *fully agree*. The scales are *fitness/health* (3 items), *appearance/physique* (3 items), *distraction/catharsis* (3 items), *activation/pleasure* (3 items), *aesthetics* (2 items), *competition/achievement* (4 items), and *contact* (5 items). Evidence towards construct and concurrent validity has been provided (Lehnert et al., 2011). In this study, reliability was .73 ≤ ω_H ≤ .92 (.72 ≤ α ≤ .92), and ω_H should be interpreted as the essentially τ-equivalent model fitted the data better ($\Delta\chi^2[23] = 469.37$, $p < .001$).

Exercise causality orientations reflect assumptions about the causality regarding the initiation and maintenance of exercise behavior. The scales *autonomy*, *control*, and *impersonal* orientation (each 4 items) were assessed using the vignette-based Exercise Causality Orientations Scale (ECOS; Rose, Markland, & Parfitt, 2001) in a German version (G-ECOS; Busch, Utesch, & Strauss, in review). Each item was rated on a 7-point Likert scale ranging from 1 = *not likely* to 7 = *very likely*. In this study, reliability was .47 ≤ ω_H ≤ .57 (.46 ≤ α ≤ .57), and both Cronbach's α and ω_H can be interpreted as the essentially τ-equivalent model did not fit the data better ($\Delta\chi^2[11] = 18.92$, $p = .062$).

Personality. To assess aspects of personality, several questionnaires were applied. One of the most prominent, overarching, and widely used conceptualization of personality is the Big Five (Costa & McCrae, 1992). The five personality dimensions were measured via a German version of the BFI-10 (Rammstedt, Kemper, Klein, Beierlein, & Kovaleva, 2012). The ten items were rated on a 5-point Likert scale ranging from 1 = *not agree* to 7 = *fully agree*. The five scales *neuroticism, extraversion, openness, agreeableness,* and *conscientiousness* each entail two items. In this study, reliability was .61 ≤ ω_H ≤ .77 (.50 ≤ α ≤ .76), and ω_H should be interpreted as the essentially τ-equivalent model fitted the data better ($\Delta\chi^2[14] = 158.43$, $p < .001$). Furthermore, scales to measure perfectionism and narcissism were applied as relations to fitness app usage have been indicated in previous studies (e.g., Hussain et al., 2017; Lupton, 2014; Morf & Rhodewalt, 2001).

Perfectionism has been identified as a dimensional constructs and is defined as a personality trait that is defined as a person's tendency to set excessively high standards of performance, accompanied by overly self-critical evaluation (Frost, Marten, Lahart, & Rosenblate, 1990). In this study, the Frost Multidimensional Perfectionism Scale was applied in a German version using the scales *perfectionistic strivings* (7 items) and *perfectionistic concerns* (13 items) that were rated on a 7-point Likert scale ranging from 1 = *not agree* to 7 = *fully agree*. Reliability in this study was ω_H = .89 (α = .89) for perfectionistic strivings, and ω_H = .86 (α = .86) for perfectionistic concerns. In this study, ω_H should be interpreted as the essentially τ-equivalent model fitted the data better ($\Delta\chi^2[7] = 59.45$, $p < .001$).

Narcissism is a personality trait that is defined as a pattern of grandiosity, self-focus, and self-importance (Morf & Rhodewalt, 2001). To measure narcissism, the narcissism scale of the Personality Style and Disorder Inventory (PSSI; Kuhl & Kazén, 2009) was used. The scale entails ten items that are rated on a 4-point Likert scale ranging from 1 = *not agree* to 4 = *fully agree*. In this study, reliability was ω_H = .75 (α = .75), and ω_H should be interpreted as the essentially τ-equivalent model fitted the data better ($\Delta\chi^2[9] = 53.92$, $p < .001$).

Statistical analysis. Data analyses were conducted via the programming language *R* (R Core Team, 2016) with the interface RStudio (RStudio Team, 2015). To assess bivariate correlations, Pearson's correlation coefficients were calculated. If one variable was dummy-coded (i.e., fitness app usage), point-biserial correlations coefficients were calculated. All correlation coefficients were interpreted as either small ($.10 \leq r < .30$), medium ($.30 \leq r < .50$), or large ($r \geq .50$; Cohen, 1992). The analysis of the open format questions regarding dropout from fitness app usage was conducted via the Critical Incident Technique (CIT; Flanagan, 1954).

Table 7

Item Characteristics of the Variables Assessed in Study A

	Range	*M*	*SD*	*SE*	Skewness	Kurtosis	ω_H	α
Duration of Usage (in weeks)								
Fitness App	0–200	41.98	62.50	3.71	3.75	23.27		
Exercise Tracking	0–200	43.50	58.13	4.23	2.52	8.41		
Nutrition Tracking	0–200	22.11	35.96	3.26	3.19	11.89		
Frequency of App Usage (min per week)	0–500	150.85	175.66	10.52	2.66	9.44		
Exercise (hours per week)	0–40	7.86	6.02	0.22	1.85	4.85		
Body Awareness								
Noticing	1–5	4.35	0.88	0.04	–0.79	1.20	.69	.69
Body Listening	1–5	3.72	1.02	0.04	–0.22	–0.09	.74	.73
Body Trusting	1–5	4.42	0.99	0.04	–0.67	0.26	.81	.81
Trust in Technology								
Reliability	1–6	3.81	1.19	0.05	–0.22	0.01	.89	.89
Functionality	1–6	3.98	1.34	0.05	–0.37	–0.17	.86	.85
Help Function	1–6	3.50	1.11	0.04	–0.27	–0.20	.82	.82
Situational Normality	1–6	3.56	1.21	0.05	–0.29	–0.25	.84	.84
Structural Assurance	1–6	3.46	1.13	0.05	–0.43	–0.32	.85	.85
Faith in General Technology	1–6	4.21	0.99	0.04	–0.66	1.07	.79	.78

Trusting Stance	1–6	4.11	1.34	0.05	–0.47	–0.46	.86	.85
Big Five								
Conscientiousness	1–7	5.37	1.01	0.04	–0.58	0.66	.67	.64
Extraversion	1–7	4.83	1.23	0.05	–0.43	–0.12	.81	.81
Agreeableness	1–7	5.38	0.94	0.04	–0.78	1.83	.61	.50
Openness	1–7	4.82	1.19	0.05	–0.38	0.03	.68	.68
Neuroticism	1–7	4.11	1.36	0.05	–0.05	–0.66	.77	.76
Perfectionistic Strivings	1–6	5.29	1.16	0.05	–0.91	0.84	.89	.89
Perfectionistic Concerns	1–6	3.70	1.33	0.05	0.07	–0.64	.86	.86
Narcissism	1–4	2.11	0.47	0.02	0.33	0.42	.75	.75
Exercise Basic Needs Satisfaction								
Autonomy	1–6	5.23	1.14	0.05	–0.96	1.23	.75	.75
Competence	1–6	5.25	1.06	0.04	–1.02	1.50	.85	.85
Relatedness	1–6	4.95	1.33	0.05	–0.76	0.34	.89	.88
Exercise Regulations								
Intrinsic	1–5	4.67	1.11	0.04	–0.88	0.42	.83	.82
Identified	1–5	5.03	0.83	0.03	–1.46	4.06	.77	.77
Introjected	1–5	3.58	1.15	0.05	–0.29	–0.45	.75	.73
Extrinsic	1–5	1.66	0.83	0.03	1.60	2.66	.74	.72
Exercise Participation Goals								
Fitness/Health	1–4	4.27	0.63	0.03	–1.32	3.45	.73	.71

Body/Appearance	1–4	3.54	1.09	0.04	–0.63	–0.38	.87	.86
Distraction/Catharsis	1–4	3.68	0.89	0.04	–0.85	0.60	.82	.82
Activation/Enjoyment	1–4	3.92	0.81	0.03	–1.21	1.83	.74	.73
Aesthetics	1–4	2.99	1.15	0.05	–0.10	–0.87	.73	.73
Competition/Performance	1–4	2.64	1.04	0.04	0.28	–0.76	.83	.82
Contact	1–4	2.88	1.13	0.05	–0.22	–1.02	.92	.92
Exercise Causality Orientations								
Autonomy	1–7	5.39	0.94	0.04	–1.07	3.42	.57	.57
Control	1–7	4.28	1.06	0.04	–0.58	0.79	.53	.52
Impersonal	1–7	3.35	0.98	0.04	0.04	0.31	.47	.46

Note. Duration of App Usage was assessed in weeks; Frequency of App Usage was assessed in hours per week; Exercise was assessed in hours per week.

Table 8

Correlation Matrix of the Variables Assessed in Study A

	Usage Fitness App	**Usage** Exercise Tracking	**Usage** Nutrition Tracking	**Duration of** Fitness App Usage	**Duration** Exercise Tracking	**Duration** Nutrition Tracking	**Frequency** Fitness App Usage	**Exercise** (hours/week)
Usage								
Fitness App	-	.60**	.28**	.36**	.35**	.16	.10	.11**
Exercise Tracking		-	.37**	.34**	.38**	.16	.10	.14*
Nutrition Tracking			-	.06	−.01	.37**	.11	−.00
Duration of Usage								
Fitness App				-	.74**	.37**	−.01	.10
Exercise Tracking					-	.46**	−.04	.15
Nutrition Tracking						-	.03	−.03
Frequency of App Usage								.04
Body Awareness								
Noticing	−.01	−.02	.04	−.01	.01	.05	.01	.12**
Body Listening	−.02	.04	.11	−.02	−.04	.02	−.05	.12**
Body Trusting	.01	−.06	−.07	.07	.07	.06	−.09	.14**
Trust in Technology								
Reliability	.27**	.11	.08	.17**	.25**	.16	.09	−.01
Functionality	.45**	.26**	.09	.27**	.22	.08	.05	.00
Help Function	.16**	.18**	.08	.08	.08	−.08	.05	.02

Situational Normality	.35**	.27**	.18**	.22**	.22**	.09	.08	–.02
Structural Assurance	.10*	.08	.07	.15*	.08	.17	.03	–.08
Faith in General Technology	.14**	.08	.03	.15*	.20**	.11	.14*	–.09*
Trusting Stance	.15**	.09	.07	.13*	.10	.06	.07	–.04
Big Five								
Conscientiousness	.01	.04	–.06	–.03	.02	–.09	–.08	.11**
Extraversion	.03	.02	.02	.12*	–.01	.10	–.11	.08
Agreeableness	–.06	–.04	–.03	–.04	–.10	–.19*	.02	.05
Openness	–.09*	–.08	.01	–.01	–.06	–.01	–.08	.01
Neuroticism	–.05	.07	.11	–.10	–.14	–.00	.04	–.15**
Perfectionistic Strivings	.07	.04	.02	.06	.05	-.02	.04	.11**
Perfectionistic Concerns	.05	.06	.11	–.03	–.06	.06	.04	.02
Narcissism	.08*	.04	.06	.16**	.15*	.25**	.01	.04
Exercise Basic Needs Satisfaction								
Autonomy	.16**	.13*	.00	.20**	.20**	–.01	.02	.27**
Competence	.14**	.04	–.07	.15*	.11	–.05	.05	.35**
Relatedness	–.00	–.07	–.11	.09	–.08	–.06	–.08	.26**
Exercise Regulations								
Intrinsic	.12**	–.01	.02	.09	–.02	–.03	–.08	.39**
Identified	.12**	.08	.06	.18**	.11	–.07	–.00	.20**

Introjected	.06	.02	.08	.02	–.03	.00	–.07	.01
Extrinsic	–.05	.02	.02	–.01	.07	.10	–.01	–.04
<u>Exercise Participation Goals</u>								
Fitness/Health	.13**	.20**	.10	.19**	.14*	.00	.05	.07
Body/Appearance	.16**	.22**	.23**	.11	.02	.09	.05	–.04
Distraction/Catharsis	.11**	.08	.00	.05	–.12	–.20*	–.02	.13**
Activation/Enjoyment	.06	.01	–.06	.11	.00	–.13	–.06	.18**
Aesthetics	.05	.01	.03	.12*	.07	.05	–.07	.18**
Competition/Performance	.13**	–.09	–.01	.12*	.01	.06	.02	.34**
Contact	–.06	–.08	–.07	–.03	–.07	–.04	.00	.26**
<u>Exercise Causality Orientations</u>								
Autonomy	.07	.08	–.02	.10	.03	–.06	.09	.14**
Control	.00	-.01	.02	.06	.01	–.17	–.04	.00
Impersonal	–.02	.07	.02	–.01	.09	.02	–.02	–.01

Note. App Usage n = 582, Duration of Usage n = 189; Correlations referring to App Usage are point-biserial correlations. Sample sizes of app usage and duration of app usage variables vary due to dropout during answering the online questionnaires (questions regarding duration and frequency of app usage were placed at the end of the questionnaires).

Results

All item characteristics are presented in Table 7. The correlations of the different aspects and categories of fitness app usage with exercise, trust in technology, personality, motivation, body trusting, and body awareness are presented in Table 8. Fitness app usage including the aspects of exercise, but not nutrition tracking displayed significant small correlations with exercise. With regards to personality (i.e., Big Five), and perfectionism, mostly insignificant correlations were found with fitness app usage and exercise. Agreeableness displayed a small negative correlation with the duration of nutrition tracking, and conscientiousness was related to exercise to a small extent. Correlations between aspects of body awareness and fitness app usage were all insignificant, and all aspects of body awareness were positively related to exercise to a small extent. Trust in technology scales were mostly significantly correlated with fitness app usage to a small to medium degree, but not with exercise. With regards to motivation, most scales measuring exercise basic needs satisfaction and exercise participation goals displayed significant positive correlations with fitness app usage to a small extent, and with exercise to a small to medium extent. However, exercise regulation modes and exercise causality orientations were mostly uncorrelated with fitness app usage and exercise.

In an additional analysis of the open format questions, the participants were asked to state why they had dropped out from using a fitness app. The full answers are provided in a supplementary file on https://osf.io/t4gfe/?view_only=61af3bab53bf4ea3837b8c4a246afbf4. The answers were categorized as follows (Figure 51): (1) it was too much effort to bring the device when exercising/to enter data into the app (30.43%); (2) general loss of interest or motivation (no further reason were given, 27.17%); (3) technical issues with the device and/or too imprecise measurement (21.74%); (4) no additional value when exercising (17.39%); (5)

too impersonal instructions that were not tailored to the participants' needs (14.13%); (6) the app was only useful as an external feedback at the beginning (8.70%); (7) the app and the instructions were too much controlling (8.70%); (8) issues with privacy (6.52%).

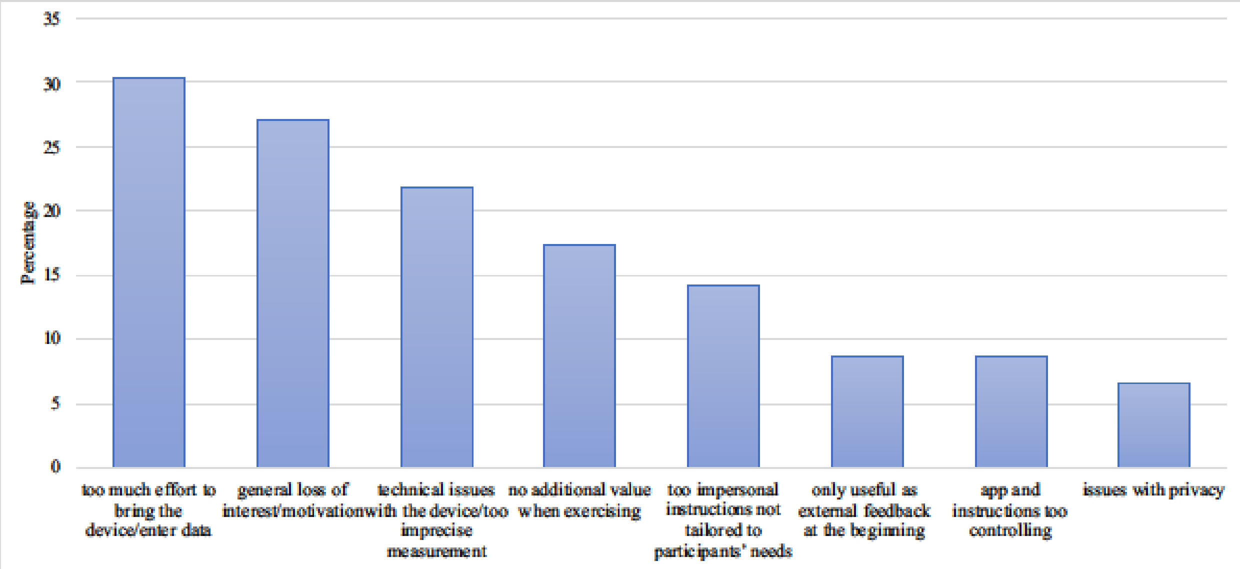


Figure 51. Categories and percentages of reasons for dropout from fitness app usage.

A subsequent calculation of bivariate correlations with sample characteristics revealed that general loss of interest/motivation was negatively associated with duration of fitness app usage ($r = -.12$, $p = .045$), and effort to bring the device when exercising/enter data into the app was negatively associated with age ($r = -.09$, $p = .039$).

Discussion

It was an aim of Part 1 to provide an evaluation of the main factors associated with dropout from fitness app usage. Beyond the background of multiple risks connected with fitness app usage (e.g., data safety, privacy issues, low reliability of data), it was assumed that trust is a key element in understanding fitness app usage.

With regards to the bivariate correlations, different aspects of trust were assessed. Trust in technology was related to both fitness app usage and duration of fitness app usage, but not to exercise. In contrast, body trusting was related to exercise, but unrelated to fitness app (i.e. technology) usage. Consequently, these findings imply that trusting is related to the context of relevance. Trust in technology has consistently been found to predict technology usage across diverse technologies, such as IT, computer programs, and general technology (Lee & See, 2004; McKnight et al., 2011; Söllner et al., 2012). Therefore, trust in technology can be regarded as a crucial factor in understanding the processes of initiation of, maintenance of, and dropout from fitness app usage. In contrast, body trusting can rather be connected with explaining body related aspects such as exercise behavior.

Looking at connections between fitness app usage and personality, it was hypothesized that fitness app usage is associated with neuroticism and narcissism. In this study, fitness app usage was largely unrelated with aspects of the Big Five and with perfectionism. In the context of general smartphone apps, the Big Five have been connected with the initiation of usage (e.g., high levels of neuroticism were found to be positively related to mobile social or shopping apps; Xu, Frey, Fleisch, & Ilic, 2016). Similarly, neuroticism was found to predict monitoring of personal health via smartphone apps and getting in social contact about health issues (Bregenzer, Wagner-Hartl, & Jiménez, 2017). With regards to specific fitness apps, previous research has provided little evidence towards a presence of connections between personality variables and fitness app usage. However, high levels of excessive exercise and a drive for thinness were found to predict fitness app usage (Chae, 2018; Elavsky, Smahel, & Machackova, 2017; Sun et al., 2016). In another study, high levels of body dissatisfaction and neuroticism were found to predict calorie tracking in fitness app users (Embacher et al., 2018), which is in contrast to the results found in this study. Regarding narcissism, positive associations with the duration of fitness app usage, exercise tracking, and calorie tracking were found. Narcissism is a personality trait that is defined as a pattern of grandiosity, self-focus, and self-importance (Morf & Rhodewalt, 2001). Previous research has indicated that *excessive* smartphone app usage is associated with narcissism

(Hussain et al., 2017). In line with these results, narcissism was largely unrelated to fitness app usage, fitness tracking, and calorie tracking *per se* in this study, but displayed significant associations with the *duration* of fitness app usage, fitness tracking, and calorie tracking. As significant connections between fitness app usage and narcissism, but not with neuroticism were found *Hypothesis 1b* was confirmed in parts.

With regards to motivation, it was hypothesized that intrinsic forms of motivation, goal achievement, and needs satisfaction are associated with fitness app usage. In this study, the overall correlation pattern indicated connections between fitness app usage and intrinsic forms of motivation, and autonomy and competence need satisfaction. Somewhat higher associations were found between fitness app usage and exercise. With regards to specific participation goals, fitness app usage was related to fitness/health, body/appearance, competition/performance, and distraction/catharsis goals. Hence, *Hypothesis 1c* was confirmed. In line with the results found in this study, fitness app usage has been connected with perceptions of accomplishment and goal attainment (i.e., autonomy and competence needs) and personal long-term goals (Clinger, 2015; Rönkkö, 2018). Molina and Sundar (2018) found that features of fitness apps eliciting basic needs satisfaction (i.e., autonomy, competence, relatedness) can predict higher exercise outcomes. Also, it was found that people track their health or fitness in order to maintain/improve fitness, to motivate themselves to exercise, to lose weight, because it is fun, or to compete with other people (GfK, 2017), which is in line with the results found in this study.

In a second step, the open format questions were analyzed that targeted the reasons for dropout from fitness app usage. The results imply that the participants mainly dropped out from using fitness apps because of technical issues, imprecise measurement or too much effort in data collection. In sum, these aspects can be related to the characteristics of a fitness app's reliability and functionality, representing core aspects in reasons for dropout from fitness app usage. Too much effort to enter data into the app might have especially been connected to the perceived functionality of a fitness app. In addition, loss of interest and motivation were other main reasons for dropout and were also associated with lower duration of fitness app usage. Loss of interest could be interpreted as a novelty effect, but the results can also hint at low intrinsic motivation and a lack of need satisfaction (i.e., autonomy, competence, relatedness; Deci & Ryan, 2000). Relatively low intrinsic and high external motivation can also be connected with the finding that the participants found the app's instructions too much controlling. In sum, the results of the analysis of the open format questions indicate that trusting beliefs represent a central aspect when investigating the factors that are associated with fitness app usage and dropout. Thus, the existence of a valid construct to analyze technology related beliefs in fitness app users might be highly relevant when further examining the use of new technologies (i.e. fitness app usage in exercise and health context).

Part 2: Propensity to Trust and Institution-Based Trust

In Part 1, trust in technology was identified as a key element that is associated with fitness app usage. Therefore, it was an aim of Part 2 to test the model of trust in technology in the field of fitness app usage and to gain elaborate understanding of the processes that are associated with the initiation and maintenance of fitness app usage. Within the model of trust in technology (McKnight et al., 2011), propensity to trust and institution-based trust describe non-specific assumptions that can be observed and can be relevant during the initiation of usage. McKnight et al. (2011) claimed the necessity to differentiate between different stages of usage when investigating trust in technology (i.e., non-usage, usage, and post-usage/dropout). However, the examination of differentiated user groups, such as non-users, users, and dropout has yet to be targeted in research based on the model of trust in technology. Therefore, it was the aim of Part 2 to examine and test the processes postulated in the model of trust in technology (McKnight et al., 2011) with regards to the initiation of fitness app usage. In doing so, a subsample was used, contrasting the groups of fitness app *users* vs. *non-users*.

Hypotheses. To test the component of *propensity to trust* and *institution-based trust* using a sample of fitness app users vs. non-users, it was hypothesized:

Hypothesis 2a: The factor structure and interrelations proposed in the model of trust in technology are valid and invariant across app users vs. non-users.

Hypothesis 2b: Propensity to trust and institution-based trust are higher in fitness-app users compared to non-users.

Methods

In Part 2, a subsample of $N_1 = 476$ was used. $N = 145$ participants (30.46%) were identified as *users*, and $n = 331$ participants (69.54%) were identified as *non-users*.

Trust in technology. Assessing propensity to trust and institution-based trust in fitness app users and non-users, the German version of the questionnaire for trust in a specific technology (Querfurth-Böhnlein, 2018) was used. The total assessment tool includes 15 items that are rated on a 7-point Likert scale ranging from 1 = *not agree* to 7 = *fully agree*. Scales measuring the sub-constructs of propensity to trust were *trusting stance in general technology* (3 items) and *faith in general technology* (4 items). Measuring institution-based trust, the scales *structural assurance* (4 items) and *situational normality* (4 items) were applied. To estimate reliability, the scales were analyzed using Mc Donald's ω_H (McDonald, 1985, 1999), because a congeneric model fitted the data of the subsample better than an essentially τ-equivalent model ($\Delta\chi^2(14) = 111.44$, $p < .001$). Reliability coefficients for the subsample ranged from $.78 \leq \omega_H \leq .87$ (Table 9).

Statistical analysis. Statistical analyses were conducted via the *System for Statistical Computation and Graphics R* (R Core Team, 2016). The coefficients indicated absence of multivariate normality ($\chi^2 = 1913.46$ for skewness [$p < .001$] and $z = 37.29$ for kurtosis [$p < .001$]). Thus, a scaled estimator was used in the SEM. In the analysis of the hypothesized model, a SEM was conducted via the *R* packages *lavaan* (Rosseel, 2012) and *semTools* (semTools Contributors, 2016). Data was inspected via Mardia tests for normality, skewness, and kurtosis (Mardia, 1985), applying the *R* package *mvn* (Korkmaz, Goksuluk, & Zararsiz, 2014). An acceptable model fit was evaluated on the basis of cut-off criteria suggested by Hu and Bentler (1999; CFI close to > .95, TLI close to > .95, RMSEA close to < .06, SRMR close to < .08).

In a subsequent multi-group analysis facing differences across *users* (n = 197) vs. *non-users* (n = 279), a measurement of invariance was conducted (Vandenberg & Lance, 2000). As a scaled χ^2 estimator had been applied in the SEM analysis, a scaled estimator (Satorra & Bentler, 2001) was also used in the measurement of invariance. In the analysis, four models were tested: (1) configural invariance: equal factor structure across the groups; (2) weak invariance: equal factor loadings across the groups; (3) strong invariance: equal factor loadings and intercepts across the groups; (4) strict invariance: equal factor loadings, intercepts, and residuals across groups; (5) equal factor loadings, intercepts, residuals, and means across groups. A significant change in the fit index compared to the previously tested model indicated non-invariance. In a next step, group differences were examined. In case of non-invariant item intercepts, it has not been recommended to compare constructs on a latent variable level (Wicherts & Dolan, 2010). Thus, modification indices including univariate test scores were calculated to identify non-invariant intercepts. In a subsequent SEM and measurement of invariance, items with non-invariant intercepts were removed from the analysis and fit indices were calculated. If strong or strict invariance was indicated, means of the variables could be compared on a latent variable level. In case of strict invariance, the mean differences between groups could be compared and interpreted via standardized *z*-values and *p*-values. Statistical analyses were conducted via the *System for Statistical Computation and Graphics R* (R Core Team, 2016) using the packages *lavaan* (Rosseel, 2012) and *semtools* (semTools Contributors, 2016). The full *R* code of the analysis is provided in a supplementary file on https://osf.io/t4gfe/?view_only=61af3bab53bf4ea3837b8c4a246afbf4.

Table 9

Item Characteristics of All Variables and Scales Including All Original Items

	Range	***M***	***SD***	***SE***	**Skewness**	**Kurtosis**	ω_H	α
Part 2 *(N_1 = 476; users & non-users)*								
Situational Normality	1–7	3.56	1.21	.05	–0.29	–0.25	.84	.84
Structural Assurance	1–7	3.46	1.13	.05	–0.43	–0.32	.87	.87
Faith in General Technology	1–7	4.21	0.99	.04	–0.66	1.07	.78	.79
Trusting Stance	1–7	4.11	1.34	.05	–0.47	–0.47	.87	.85
Part 3 *(N_2 = 266; users & dropout)*								
Reliability	1–7	3.80	1.19	.05	–0.21	0.00	.88	.88
Functionality	1–7	3.98	1.34	.05	–0.36	–0.17	.82	.83
Help Function	1–7	3.50	1.11	.04	–0.27	–0.21	.79	.79
Duration Fitness App Usage (weeks)	0–200	35.62	44.01		1.87	3.17	-	-
Frequency Fitness App Usage (min/week)	0–500	121.49	108.76		1.23	1.14	-	-

Note. In order to facilitate comparisons with previous studies, α is reported in addition to ω_H.

Results

The item characteristics and reliability coefficients of the assessed variables are presented in Table 9. With regards to the SEM, a good model fit was indicated (N_1= 476, χ^2 = 234.30, *df* = 84; $p < .001$; CFI = .95, TLI = .93; RMSEA = .069 [.059;.080]; SRMR = .051, Figure 52).

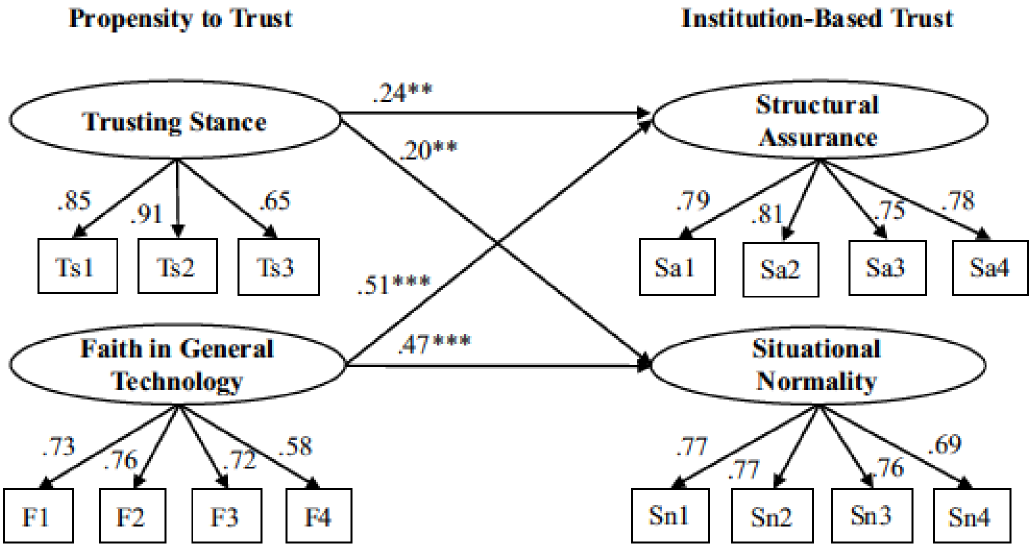


Figure 52. Results of the SEM conducted in Part 2.
Note: SEM, structural equation modelling; all factor loadings are $p < .001$.

Explained variance was R^2 = .38 in situational normality and R^2 = .55 in structural assurance. Standardized factor loadings were $.72 \leq \lambda \leq .91$ (all $p < .001$). Results of the measurement of invariance indicated invariant loadings across groups, and non-invariant intercepts and means across groups (Table 10). Thus, weak invariance was indicated, and therefore, it was not statistically valid to compare means on the latent level (Wicherts & Dolan, 2010). Modification indices revealed non-invariant intercepts for all four items of the *situational normality* scale (all $p < .001$) and for one item of the *structural assurance* scale (SA1 *"I feel okay using a fitness app because they are backed by vendor protections."*; $p <$

.001). These items were subsequently removed from the model. A following SEM showed good fit indices (N_1= 476, χ^2 = 68.41, *df* = 32; $p < .001$; CFI = .98, TLI = .97; RMSEA = .057 [.038;.076]; SRMR = .047), and the measurement of invariance indicated strict invariance (Table 10). Thus, the means could now be compared on the latent level. The comparison of means revealed that means of *structural assurance* and *faith in general technology* were both lower in non-users compared to users (all $p < .001$; Table 11).

Table 10

Results of the Measurements of Invariance Conducted in Part 2 Facing Propensity to Trust and Institution-Based Trust

		SEM (N_1 = 476)					Subsequent SEM (N_1 = 476)				
Invariance	**Δ Model**	χ^2	*df*	*p*	**CFI**	**RMSEA**	$\Delta\chi^2$	*df*	*p*	**CFI**	**RMSEA**
Configural		378.36	168		.941	.073	137.49	64		.966	.069
Weak	Loadings	**Δ 7.50**	**11**	**.757**	**Δ .001**	**Δ .003**	Δ 5.98	7	.542	Δ .000	Δ .004
Strong	Intercepts	Δ 89.80	11	< .001	Δ .022	Δ .010	Δ 7.31	7	.397	Δ .000	Δ .003
Strict	Residuals	Δ 39.54	15	< .001	Δ .007	Δ .000	**Δ 14.86**	**10**	**.137**	**Δ .002**	**Δ .002**
	Means	Δ 107.21	4	< .001	Δ .029	Δ .011	Δ 18.73	3	< .001	Δ .007	Δ .005

Note. SEM, Structural Equation Model. Bold, indicated level of invariance. Δ change in fit indices; *p* refers to $\Delta\chi^2$; Subsequent SEM Items with non-invariant intercepts removed.

Table 11

Mean Differences for Dropout and Non-Users Compared to Users

Part 2 ($N_1 = 476$)	**Means App Users (*n* = 248)**		**Mean difference Non-users (*n* = 338)**			
Scale	**Estimate**	***SE***	**Estimate**	***SE***	***z***	***p***
Reliability	4.27	.093	–0.57	.132	–4.32	< .001
Functionality	4.87	.065	–1.14	.138	–8.25	< .001
Helpfulness	3.75	.078	–0.47	.135	–3.48	.001
Part 3 ($N_2 = 266$)			**Mean difference Dropout (*n* = 168)**			
			Estimate	***SE***	***z***	***p***
Trusting Stance	4.41	.075	–0.45	.128	–3.54	< .001
Faith in General Technology	4.43	.050	–0.38	.095	–3.40	< .001
Structural Assurance	3.64	.105	–0.19	.108	–1.72	.085

Note. Unstandardized mean differences, range 1–7. Structural Assurance Item SA1 excluded.

Discussion

In Part 2, it was the aim to provide construct validity regarding the assumed process and group differences regarding propensity to trust and institution-based trust in fitness apps among *fitness app users* vs. *non-users*. Good internal consistency, acceptable model fit, and high explained variance were found. Consequently, the results provide support for the validity of the four-factor structure of propensity to trust and institution-based trust in fitness apps. Specifically, high levels of trusting stance and faith in general technology both led to higher levels of structural assurance and situational normality. The results indicate that a person's general propensity to trust technology is a first indicator leading to trusting beliefs in a specific context (i.e., institution-based trust). With regards to the measurement of invariance, evidence for equal factor structure and equal loadings was provided across fitness app users vs. non-users, indicating similar trust related processes across different populations. Therefore, *Hypothesis 2a* was confirmed. The results are in line with the factor structure and the processes assumed by McKnight et al. (2011).

However, weak invariance indicated differences in intercepts across app users vs. non-users. In a subsequent analysis excluding items with non-invariant intercepts, strict invariance was indicated, providing validity of the measurement. Regarding propensity to trust, the means of trusting stance and faith in general technology were higher in users compared to non-users. Therefore, propensity to trust in general technology can be interpreted as an indicator to predict the initiation of fitness app usage. Regarding institution-based trust, all items of the situational normality scale revealed non-invariant intercepts across the groups of users vs. non-users. Thus, differences in meanings of the items or specific response sets might have been present. Situational normality reflects the belief that usage of a technology is normal and pleasant. Consequently, the assessment of situational normality might not be an adequate scale when measuring initial trust in a population of non-users. Regarding structural assurance, results indicate that the adjusted scale is appropriate in investigating differences in users vs. non-users. However, means were not different across groups, indicating that beliefs about legal assurance (e.g., consumer rights, data security) might not be of high relevance in explaining the initiation of fitness app usage. Thus, *Hypothesis 2b* was confirmed in parts. In sum, a general trusting stance towards technology might predict the initiation of fitness app usage, whereas more technology specific beliefs (e.g., in consumer rights) might not. In this context, beliefs about consumer rights and normality of usage potentially requires knowledge-based experience with the technology, and therefore are not useful to predict the initiation of usage in non-users. In sum, the scales measuring propensity to trust can be validly measured in both fitness app users and non-users. However, the scales measuring institution-based trust (i.e., structural assurance and situational normality) revealed issues with the validity. Furthermore, the scales measuring institution-based trust cannot be validly measured in a sample of persons who are unexperienced in fitness app usage.

Part 3: Trusting Beliefs

The results from Part 2 indicate that propensity to trust can contribute to understanding the *initiation* of fitness app usage, whereas the scales measuring institution-based trust are of limited validity. In Part 3, it was the aim to understand the process of *maintenance* and *dropout* from fitness app usage, applying the scales of trusting beliefs in technology. Trusting beliefs describe assumptions of the trustor that can be observed during or after experiencing interaction with the trustee or trusted technology, for example with fitness apps. (McKnight et al., 2011). Therefore, it was the aim of Part 3 to examine the processes postulated in McKnight et al. (2011) of trusting beliefs in fitness apps and their influence on duration and frequency of fitness app usage. In doing so, trusting beliefs regarding fitness app usage were analyzed in a subsample of fitness app *users* vs. *dropout*.

Thus, by testing the model of trust in technology, the effects of trusting beliefs on duration of fitness app were examined via SEM. However, when attempting to understand the process of dropout from fitness app usage, the application of more specific methodological approaches can lead to incremental insight regarding the factors that influence the maintenance of and dropout from fitness app usage. In this context, survival analyses can be a highly useful tool to analyze the duration until an event occurs. Survival analyses have successfully been used to examine predictors of survival rates, for example in the evaluation of cancer treatment (Fizazi et al., 2012; Győrffy et al., 2010). Therefore, it was an aim to conduct additional analysis via a survival analysis. In further analysis, it was also an aim to provide an exploration of the role of institution-based trust that had stayed unclear throughout Part 2. Specifically, institution-based trust is a concept that has been defined as and found to be a predictor of *trusting beliefs* in technology, but not of *actual usage* (Mcknight, et al., 2011). Although institution-based trust represents a concept of initial trust, the results of Part 2 indicate that the scales measuring institution-based trust include content that is related to current usage (i.e., usage feels normal or data security gives a good feeling). Therefore, it was assumed that institution-based trust cannot be validly evaluated in non-users but might be worth to be explored in experienced users only. McKnight et al. (2011) made clear that trusting beliefs (i.e., reliability, functionality, helpfulness), but not propensity to trust or institution-based trust are associated with intention to use and deep-structure usage. However, although not specified in the model, it was of interest to explore whether institution-based trust measured in experienced fitness app users can predict survival in fitness app usage. Therefore, the present analysis is an exploratory approach on the field of trusting beliefs in fitness apps going beyond the model postulated by McKnight et al. (2011).

A third aim of Part 3 was to look at the role of body trusting in the context of fitness app usage. Fitness apps have been designed to enhance physical activity, such as exercise. Therefore, there are two important aspects of trust, namely trust in technology and body trusting for understanding processes of initiation and maintenance of and dropout from fitness app usage. These aspects are relevant in both contexts of (A) fitness app usage and (B) exercise (Figure 53).

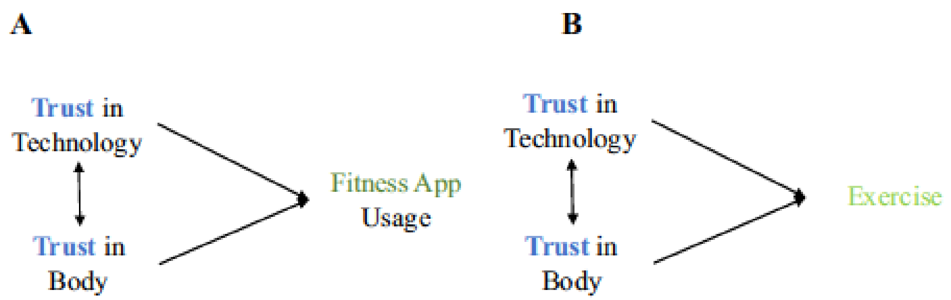


Figure 53. Visualization of the research question targeting the influence of trust in technology and body trusting on (A) Fitness app usage and (B) exercise behavior.

Yet, it has stayed unclear how trust in technology and body trusting interact and under which circumstances and to what extent their interaction influences fitness app usage and exercise. Advancing designs based on bivariate covariance matrices, more sophisticated methodology can be beneficial to reveal such potentially multifarious interrelations. Targeting the effects of two variables and considering the degree of their difference, the methodology of response surface analysis (RSA) has been established (Edwards, 2002, 2007). Based on polynomial regression analysis, the differential effects of two related predictor variables (e.g., body trusting and trust in technology) on an outcome variable (e.g., fitness app usage or exercise) can be displayed in a three-dimensional space. RSA has been suggested as an approach to examine moderation and to overcome statistical limitations of difference scores (Shanock, Baran, Gentry, Pattison, & Heggestad, 2010). RSA has been applied to various fields, including work psychology, personality psychology, and sport and exercise psychology (Harris, Anseel, & Lievens, 2008; Humberg, Nestler, & Back, 2018; Utesch, Dreiskämper, Naul, & Geukes, 2018). In this study, it could be examined how trust in technology and body trusting affect fitness app usage and exercise behavior, depending on various combinations of the variables' levels. Within an RSA analysis, it could be analyzed how the *congruence* of two related variables (i.e., trust in technology and body trusting) affects the degree of fitness app usage or exercise. Furthermore, it can be examined how the *incongruence* of two related variables (i.e., trust in technology and body trusting) affects the degree of fitness app usage or exercise.

Hypotheses. Testing the component of *trusting beliefs* using a sample of fitness app users vs. dropout, it was hypothesized:

Hypothesis 3a: The factor structure proposed in the model of trust in technology is valid and invariant across app users vs. dropout.

Hypothesis 3b: Trusting beliefs in fitness apps can predict the duration of fitness app usage and frequency of fitness app usage.

Hypothesis 3c: Reliability, functionality, and helpfulness are higher in fitness-app users compared to dropout.

Hypothesis 4: Reliability, functionality, helpfulness, structural assurance, and situational normality can predict higher survival rates in fitness app usage.

Hypothesis 5: Trust in technology and body trusting are related and the effects of congruence and incongruence to explain fitness app usage and exercise behavior are explored.

Methods

In Part 3, a subsample including $N_2 = 266$ participants was used. $N = 145$ participants (54.51%) were identified as *users*, and $n = 121$ participants (45.49%) were identified as *non-users*.

Trust in technology. Analogue to the analysis of Part 2, the questionnaire for trust in a specific technology (McKnight et al., 2011) was used. Measuring trusting beliefs in a specific technology, the scales *reliability* (4 items), *functionality* (3 items), and *helpfulness* (4 items) were applied and were measured on a 7-point Likert scale ranging from 1 = *not agree* to 7 = *fully agree*. In the reliability analysis, the congeneric model fitted the data of the subsample better ($\Delta\chi^2(10) = 37.97$, $p < .001$). Thus again, ω_H was calculated. Reliability coefficients of this subsample ranged from $.79 \leq \omega_H \leq .88$ (Table 9).

Statistical analysis. Statistical analysis regarding the SEM was identical to the analysis in Part 2. In tests for multivariate normality, coefficients were $\chi^2 = 2076.28$ for skewness ($p < .001$) and $z = 27.84$ for kurtosis ($p < .001$), indicating an absence of multivariate normality. Therefore, a scaled estimator was applied. Based on theoretical assumptions and previous validation studies (McKnight et al., 2011), the three scales measuring trusting beliefs in a specific technology were assumed to interrelate. Furthermore, paths were entered from each latent variable to duration of app usage and frequency of app usage. Analogue to the analysis of Part 2, a measurement of invariance facing differences across fitness apps users vs. dropout was conducted. If configural invariance was indicated, differences in loadings were compared across the two groups. If only paths between latent factors and dependent variables were different across the groups, a subsequent CFA was conducted to examine invariance regarding the original measurement model. If strong or strict invariance was indicated, a comparison of the mean difference was conducted.

Survival analysis. A subsequent survival analysis was conducted using the duration of fitness app usage as the outcome variable, and the scales reliability, functionality, helpfulness, structural assurance, and situational normality as predictors of survival in fitness app usage. Survival analyses have been shown to be a highly useful tool to analyze the duration until an event occurs (Allison, 2010; Singer & Willett, 1993). Survival analyses have been successfully used to examine predictors of survival, e.g., in the evaluation of cancer treatment or dropout from high school (Fizazi et al., 2012; Györffy et al., 2010; Plank, DeLuca, & Estacion, 2008). To examine the duration of fitness app usage and predictors on dropout from fitness app usage, Cox-Hazard-Survival analyses were conducted. Therefore, the data of current app users was right-censored, and the following formula was applied:

$$h(t) = h_0(t)\exp(\beta' x)$$

The estimated coefficients β represent the change in the expected log of the hazard ratio, relative to one-unit change in the predictor variable and holding all other predictors constant. Therefore, positive coefficients indicate an increase in risk of dropout given that the predictor variable increases, whereas negative coefficients indicate a decrease in the risk of dropout given that the predictor variable increases. Analogously, a risk ratio larger than one indicates an increased risk of dropout, and a risk ration smaller than one indicates a reduced risk of dropout. Statistical analyses were conducted via the R package *survival* (Therneau, 2019).

RSA. Targeting the effects of two variables on an outcome variable and considering differentiated effects depending on the predictor variables' interrelations, the methodology of RSA (Edwards, 2002, 2007) was applied. RSA advances traditional regression analyses, as differentiated effects of the two predictor variables on the outcome variable can be analyzed depending on the degree of their congruence (Humberg et al., 2018). Based on polynomial regression analysis, the differential effects of two predictor variables on an outcome variable can be displayed in a three-dimensional space. Within the three-dimensional visualization of an RSA, the shape of the surface is guided by the lines of congruence and incongruence. Effects of congruence can be made visible via a line of congruence (LOC). Similarly, effects of incongruence between the two predictor variables on the outcome variable can be assessed and made visible via a line of incongruence (LOIC). So, to speak, the LOC visualizes the effects on the outcome variable given that values of body trusting and trust in technology are in *congruence* (e.g., trust in technology and body trusting are *both* high, or *both* low). In contrast, the LOIC visualizes the effects on the outcome variable for when values of body trusting and trust in technology are *incongruent* (e.g., body trusting is low while trust in technology is high, or vice versa). First, a polynomial regression model was fitted to the data with the variables $X =$ body trusting, and $Y =$ trust in technology:

$$Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2$$

The shape of the surface above the LOC is described as $Z = b_0 + a_1X + a_2X^2$, and the shape above the LOIC is described as $Z = b_0 + a_3X + a_4X^2$, whereas the coefficients a_4 to a_4 result from more complex statistical calculations based on b_1 to b_5 (Humberg et al., 2018). The first principal axis is a linear equation that relates one predictor variable to the other. The position of the first principal axis is defined as $Y = p_{10} + p_{11}X$, where the coefficients p_{10} and p_{11} can be calculated from the coefficients b_1 to b_5. Congruence effects can be assumed if the following four conditions are met: (1) the intercept (indicated by p_{10}) is close to 0, and (2) the slope is close to 1 (indicated by p_{10}). Furthermore, congruence effects can be assumed if (3) a_3 does not significantly differ from 0, indicating that the ridge of the surface is not shifted away from the LOC, and (4) a_4 is larger than 0, indicating that the surface has no shape of an inverted U-shaped parabola. In contrast, effects of incongruence can be assumed if (1) a_3 is significantly different to 0, and if (2) a_4 is significantly negative. For RSA analyses, it has been recommended to use a sample size that is two or three times as large as a required sample size for a regression analysis with two predictors (Humberg et al., 2018). Defining a medium effects size of f^2 = .17, a desired statistical power level of .80, a probability level of α = .05, it was estimated that a minimum sample size for a regression analysis with two predictors was n = 60 (Soper, 2012). Thus, a minimum sample size between n = 120–180 was required to conduct the RSA. In the RSA, a polynomial regression model was fit to the data and the coefficients related to the lines of congruence and incongruence were evaluated. The outcome variables were log transformed due to the distribution characteristics identified in Part 1. Statistical analyses were conducted via the *R* package *RSA* (Schönbrodt & Humberg, 2018).

Results

The participants stated that they had used a fitness app for a duration of M = 35.62 weeks (SD = 44.01) and for M = 121.49 minutes per week (SD = 108.76). The item characteristics of the assessed variables and reliability coefficients are presented in Table 9.

Model of trust in technology. The results of the SEM indicated a good model fit (N_2 = 266, χ^2 = 71.33, df = 57; p = .096; CFI = .99, TLI = .98; RMSEA = .033 [.000;.056]; SRMR = .045; Figure 54).

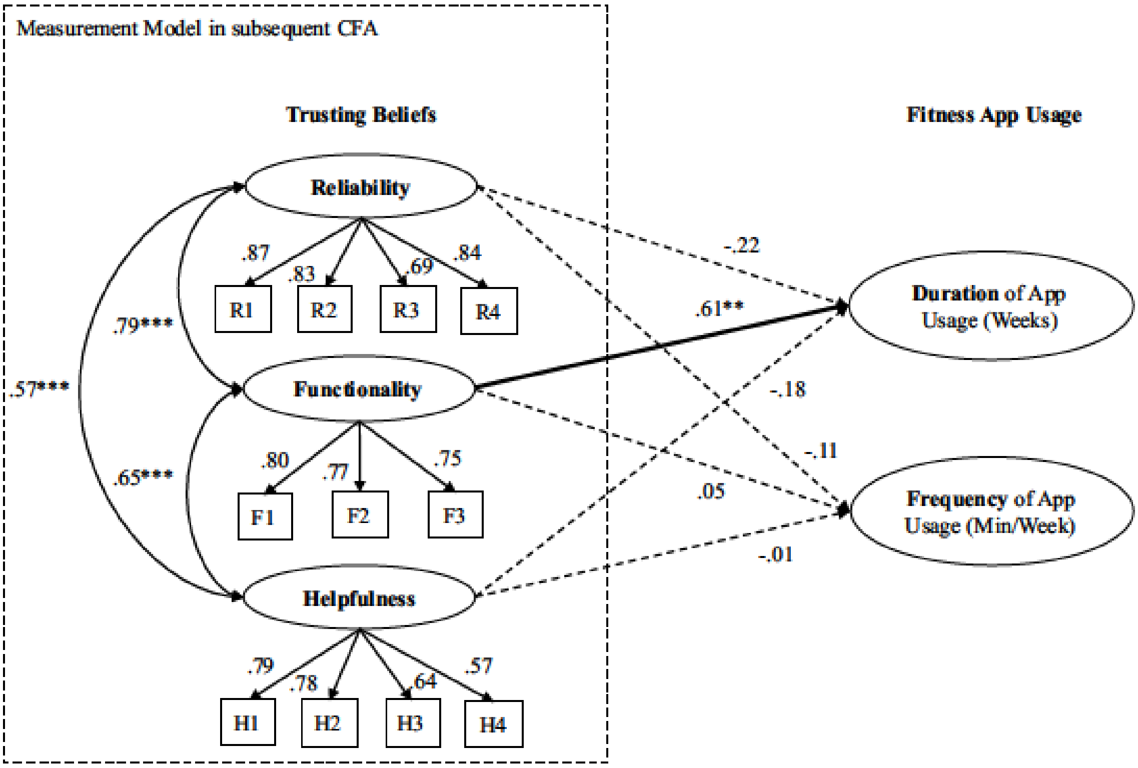


Figure 54. Results of the SEM conducted in Part 3 including a visualization of the subsequent CFA.

Note: SEM, structural equation modelling, CFA, confirmatory factor analysis; all factor loadings are $p < .001$.

Standardized factor loadings were $.64 \leq \lambda \leq .87$ (all $p < .001$). In duration of fitness app usage, $R^2 = 16.6\%$ was explained by trusting beliefs in fitness apps. In frequency of usage, $R^2 = 6.1\%$ was explained by trusting beliefs in fitness apps. The measurement of invariance indicated non-invariance regarding loadings, intercepts and means across groups (Table 12). Further examination of the loadings in each group (app users vs. dropout) revealed that the path from *functionality* to *duration of fitness app usage* was only significant in the group of non-users. All factor loadings were significant ($p < .001$) in both groups. In a subsequent analysis, only the measurement model of the SEM was subject to a CFA and a following measurement of invariance, as indicated by the dashed lines in Figure 54. In the subsequent CFA, a good model fit was indicated ($N_2 = 342$, $\chi^2 = 65.57$, $df = 41$; $p = .009$;

CFI = .98, TLI = .98; RMSEA = .048 [.024;.058]; SRMR = .047). The measurement of invariance revealed that the loadings, intercepts, and standard errors were equal across groups, now indicating strict invariance (Table 12). Thus, comparable factor structures could be assumed across the groups, and mean differences on the latent factor could be compared. Specifically, the means of *reliability*, *functionality*, and *helpfulness* were all lower in dropout compared to users (all $p \leq .001$; Table 11).

Table 12

Results of the Measurements of Invariance conducted in Part 3 facing Trusting Beliefs

		SEM (N_2 = 266)					Subsequent CFA (N_2 = 342)				
Invariance	**Δ Model**	χ^2	*df*	*p*	**CFI**	**RMSEA**	χ^2	*df*	*p*	**CFI**	**RMSEA**
Configural		**133.49**	**144**		**.985**	**.036**	117.49	82		.979	.050
Weak	Loadings	Δ 23.40	8	.003	Δ .012	Δ .011	Δ 13.66	8	.091	Δ .003	Δ .001
Strong	Intercepts	Δ 30.07	10	< .001	Δ .015	Δ .010	Δ 12.15	8	.145	Δ .002	Δ .000
Strict	Residuals	Δ 31.90	13	.002	Δ .014	Δ .006	**Δ 11.81**	**11**	**.378**	**Δ .000**	**Δ .002**
	Means	Δ 64.94	3	< .001	Δ .047	Δ .021	Δ 67.78	3	< .001	Δ .038	Δ .026

Note. SEM, Structural Equation Model. Bold, indicated level of invariance. Δ change in fit indices; *p* refers to $\Delta\chi^2$.

Survival analysis. With regards to the survival analysis of fitness app usage, the results indicate a survival probability of 50% after 73 weeks (Figure 55). The predictor effects of institution-based trust and trusting beliefs on the survival of fitness app usage are presented in Table 13.

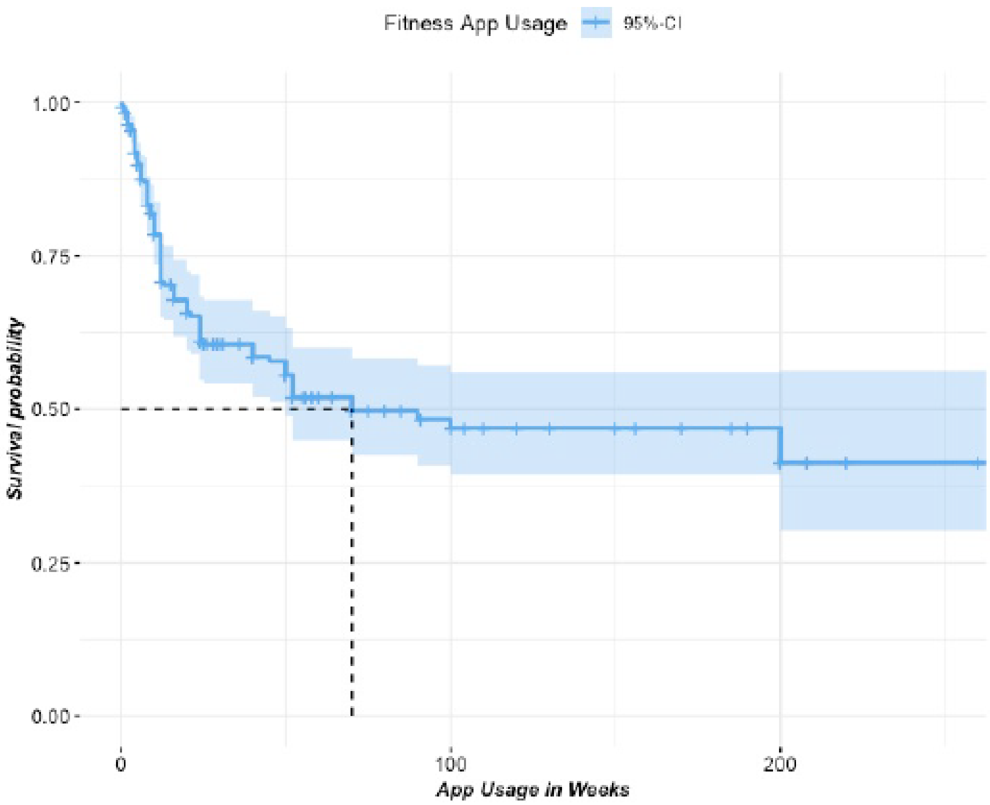


Figure 55. Survival probability of fitness app usage.
Note: 95%-CI, 95%-Confidence Interval.

When analyzing the predictor effects of the variables, high levels of situational normality were a significant predictor of survival in fitness app usage ($b = -.45$, $p < .001$), whereas structural assurance was not. With regards to trusting beliefs, high levels of functionality beliefs ($b = -.49$, $p < .001$) and low levels of helpfulness ($b = .24$, $p = .03$) predicted survival in fitness app usage. Reliability beliefs did not significantly predict dropout from fitness app usage.

Table 13

Results of the Effects on the Survival of Fitness App Usage

	Estimate	***SE***	**Exp(*b*)**	**95%-CI**	***p***
Trusting Beliefs					
Functionality	–0.49	0.11	0.61	[0.50, 076]	< .001***
Reliability	0.11	0.11	1.12	[0.90, 1.39]	.309
Helpfulness	0.24	0.11	1.28	[1.02, 1.60]	.033*
Institution-Based Trust					
Structural Assurance	0.13	0.10	1.13	[0.94, 1.37]	.189
Situational Normality	–0.45	0.14	0.63	[0.48, 0.84]	.001**

Note. b, estimate; Exp(*b*) indicates the hazard ratio for dropout; CI, confidence interval.

RSA. The results of the RSA are provided in Table 14. In the analysis identifying the effects of body trusting and trust in technology on fitness app usage, a main effect of trust in technology was observed ($b_2 = .35$, $p < .001$). However, no relations between body trusting and trust in technology and fitness app usage were observed. Testing a potential congruence effect, the intercept of the first principal axis did not differ significantly from 0, and the slope did not differ significantly from 1, meeting the first two conditions of a congruence effect. Testing whether the surface above the LOIC had an inverted U-shape, a_4 was not significantly negative, but a_3 was significantly different from 0. Therefore, the third, but not the fourth conditions were met, contradicting a congruence effect. Testing a potential effect of incongruence, a_4 was not significantly smaller than 0, indicating absence of an inverted U-shape, and absence of an incongruence effect. In sum, only one predictor (i.e., trust in technology) was related with fitness app usage, and neither congruence nor incongruence effects were found. A visualization of the RSA is presented in Figure 56.

Table 14

Results of the Response Surface Analysis

	Fitness App Usage				Exercise				
	Estimate	***SE***	**95%-CI**	***p***	**Estimate**	***SE***	**95%-CI**	***p***	**Explanation**
Regression Model									
b_0 (Intercept)	2.89	0.10	[2.71, 3.08]	< .001***	1.78	0.05	[1.68, 1.88]	< .001***	Intercept of the regression
b_1 (~bodytrust)	–0.07	0.07	[–0.22, 3.08]	.308	0.07	0.04	[–0.00, 0.14]	.066	Regression coefficient
b_2 (~techtrust)	0.35	0.07	[0.22, 0.49]	< .001***	0.01	0.02	[–0.04, 0.05]	.799	Regression coefficient
b_3 (~bodytrust^2)	0.00	0.00	[–0.01, 0.01]	.633	0.04	0.03	[–0.02, 0.10]	.167	Regression coefficient
b_4 (~bodytrust*techtrust)	–0.02	0.03	[–0.07, 0.03]	.423	0.01	0.03	[–0.04, 0.06]	.789	Regression coefficient
b_5 (~techtrust^2)	0.05	0.05	[–0.04, 0.14]	.251	0.00	0.00	[–0.00, 0.00]	.895	Regression coefficient
Position of Principal Axis									
p_{10} (Intercept)	–3.04	3.51	[–9.92, 3.84]	.386	–10.17	37.87	[–84.39, 64.05]	.788	Intercept of first principal axis
p_{11} (Slope)	–4.77	4.81	[–14.19, 4.64]	.320	0.08	0.31	[–0.53, 0.69]	.792	Slope of first principal axis
Shape of the Surface									
a_1 (LOC)	0.28	0.10	[0.08, 0.50]	.006**	0.07	0.05	[–0.02, 0.16]	.114	Linear additive effect on LOC?
a_2 (LOC)	0.03	0.03	[–0.04, 0.10]	.352	0.05	0.04	[–0.03, 0.13]	.238	Is there a curvature on the LOC?
a_3 (LOIC)	–0.43	0.10	[–0.62, –0.23]	< .001***	0.06	0.04	[–0.04, 0.11]	.106	Ridge shifted away from LOC?
a_4 (LOIC)	0.08	0.07	[–0.06, 0.21]	.265	0.04	0.04	[–0.02, 0.10]	.173	General effect of incongruence?

Note. bodytrust, body trusting; techtrust, trust in technology; LOC, line of congruence; LOIC, line of incongruence.

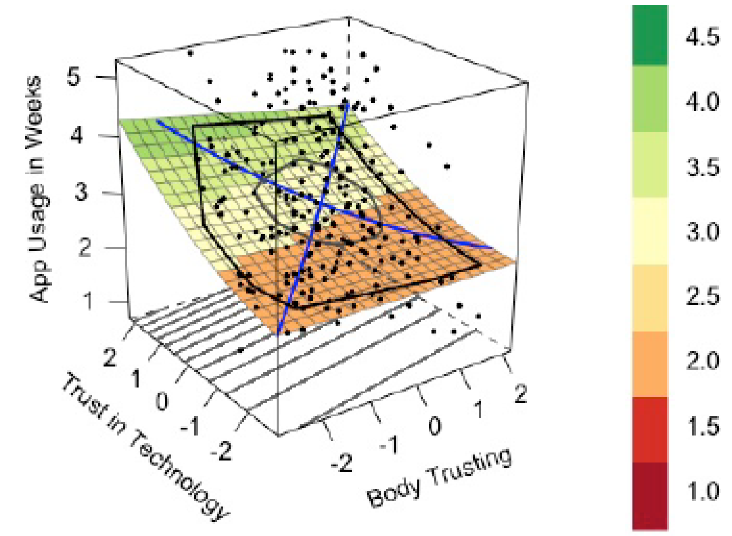


Figure 56. Visualization of the RSA analysis of trust in technology and body trusting on fitness app usage.

In the analysis identifying the effects on exercise, neither effects of trust in technology, nor of body trusting were observed. Therefore, no effects of congruence or incongruence could be observed either. A visualization of the RSA is presented in Figure 57.

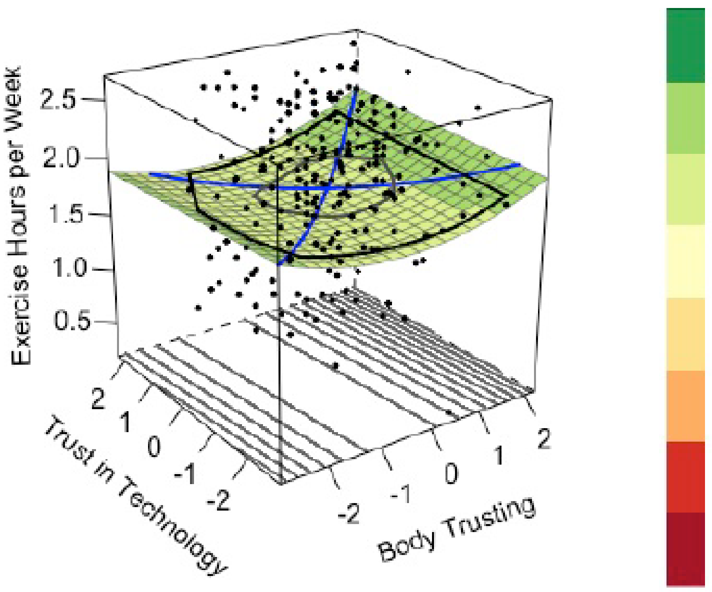


Figure 57. Visualization of the RSA analysis of trust in technology and body trusting on exercise.

Discussion

It was the aim of Part 3 to test the aspects of *trusting beliefs* in the field of fitness app usage. Thus, it was a purpose to understand how duration and frequency of fitness app usage among *fitness app users* vs. *non-users* are affected by trust related processes in the context of maintenance of usage and dropout from fitness app usage. Therefore, three different and complimentary methodologies were used.

Model of trust in technology. Using SEM to test the trust in technology model, it was hypothesized that the factor structure proposed in the model of trust in technology is valid and invariant across app users vs. dropout. Examination of the internal consistency and SEM indicated strong evidence of a good model fit and thus provided support for the validity of the measurement of trusting beliefs in fitness apps. Therefore, *Hypothesis 3a* was confirmed. Fitness app usage represents an act of trust which is assumed to be influenced by trusting beliefs (e.g., Mayer et al., 1995). Across various studies, it has been demonstrated that trusting beliefs affect the act of trust, for example when taking risks in business relations or in task performance (Colquitt et al., 2007; Gill et al., 2005). With regards to technology specific acts, trusting beliefs in a specific technology have been shown to predict intentions and usage of technology on the field of computer programs (McKnight et. al, 2011). Therefore, it was hypothesized that trusting beliefs in fitness apps can predict the duration of fitness app usage and frequency of fitness app usage. The results found in this study indicated that lower perceived functionality of fitness apps lead to shorter durations of fitness app usage in persons who had dropped out from fitness app usage. However, the results also indicate that trusting beliefs in fitness apps cannot predict the *frequency* of fitness app usage. Frequency of usage reflects the intensity of usage and might be regarded as a distinct construct that cannot be associated with trusting beliefs in fitness apps. In sum, *Hypothesis 3b* was confirmed in parts. The analyses of mean differences revealed that reliability, functionality, and helpfulness were all higher in fitness app users compared to dropouts. Again, the mean differences imply that high perceived functionality of a fitness app shows the highest association with fitness app usage among trusting beliefs. The results also imply that the perception of reliable measurement that is flawless and consistent is of relevance in understanding the maintenance of fitness app usage. Furthermore, the results imply that help functions can be beneficial to support perceived trustworthiness in fitness app users. Thus, *Hypothesis 3c* was confirmed.

Overall, the results led to the conclusion that perceived functionality is a central aspect in maintenance of fitness app usage and is of higher relevance than reliability and helpfulness beliefs. In this context, it might be of interest to identify specific app characteristics associated with perceived functionality. For example, Lee and Cho (2016) found high levels of networkability, credibility, comprehensibility, and trendiness predicting the intention to continue using fitness apps. Furthermore, the provision of a help function in a fitness app might be of additional relevance in maintenance of fitness app usage. In sum, the results provide further support for construct and predictive validity of the assessment tool measuring trusting beliefs in a specific technology.

Survival analysis. The results of the SEM indicate that trusting beliefs can predict a longer duration of fitness app usage. To gain more detailed insight into the predictors of dropout from fitness app usage, additional survival analyses were conducted. The overall survival probability of fitness app usage indicated that 50% of the users dropped out from fitness app usage after 73 weeks. Thus, it can be assumed that about half of fitness app users would decline from usage after slightly more than one year.

With regards to trusting beliefs, perceived functionality was a strong positive predictor of survival in fitness app usage in both SEM and survival analysis, indicating that functionality beliefs are of central relevance when attempting to understand the maintenance of and dropout from fitness app usage. Reliability was not found to predict survival in fitness app usage. Therefore, it can be assumed that this aspect of trusting beliefs can be considered of little relevance in explaining fitness app usage. While perceived helpfulness was not associated with longer duration of fitness app usage in the SEM analysis of Part 3, perceived helpfulness was found to *negatively* predict survival in fitness app usage to a small degree in the survival analysis. In combination with the results found in the SEM, these results should be interpreted with care. In sum, the analysis was based on the same data set, and the differences in results can be due to an artefact of the statistical method. I.e., in SEM suppressor effects based on interrelations of predictors can yield different results than a consideration of variables in polynomial regressions, as conducted in survival analyses. Also, it is likely that changes in the importance of each dimension of trusting beliefs exist that can be made visible via the application of diverse and complementary methodologies. For example, it has been indicated that ability (functionality in the technology context) beliefs are mainly relevant during *early* stages of trust, whereas benevolence (help function in the technology context) beliefs emerge with experience and are mainly relevant during *later* stages of trust (e.g., Lewicki & Bunker, 1996; Mayer et al., 1995). Therefore, the results found in this study indicate that the importance of aspects of trusting beliefs can change in importance over time.

Going beyond the model postulated by McKnight et al. (2011) it was also of interest to examine whether institution-based trust measured in experienced fitness app users can predict survival in fitness app usage. The results indicate that situational normality, i.e., the perception of usage as normal and comfortable, can negatively predict dropout from fitness app usage. Situational normality reflects a perception of regularity in fitness app usage and might therefore be likely to occur during longer duration of fitness app usage. In contrast, structural assurance, i.e., the assumption about consumer rights, cannot predict dropout from fitness app usage. Potentially, assumptions about data security, consumer rights, etc. might be relevant when deciding for or against the *initiation* of usage, but not when deciding to *cease* from usage. Furthermore, it is to be considered that all users and dropout had made the decision to use a fitness app in the past. Therefore, the persons who were examined might have underlaid mechanisms of cognitive consistency (Webster & Kruglanski, 1994), i.e., the cognitive discomfort of a person holding contradictory beliefs, actions, or values. Once one has started to use a technology, one would rather not like to preoccupy with the risks of usage that contradict the decision to engage in usage. Cognitive consistency has been shown to be a relevant issue in the evaluation of trust in trusting relationships (Acar-Burkay, Fennis, & Warlop, 2014).

In sum, high specific trust related assumptions about the functionality of a fitness app and perceptions of normality of usage can lead to longer duration of fitness app usage. Therefore, users could be advised to use those fitness apps matching their personal needs and preferences with regards to a broad range of app functions and make usage easy to integrate into everyday life. However, it stays unclear whether situational normality can be enhanced via target group specific app functions, is a simple artefact of longer duration of fitness app usage, or both.

RSA. An RSA was conducted to shed light onto the associations between body trusting, trust in technology, fitness app usage, and exercise, and to better understand the role of trust in body trusting. It was hypothesized that trust in technology and body trusting are related, and their interaction to explain fitness app usage and exercise behavior was explored. The results found in the RSA indicate that first, trust in technology is related with fitness app usage, but not with exercise, and body trusting is unrelated with trust in technology, fitness app usage, and exercise. Second, no effects of congruence or incongruence of body trusting and trust in technology on fitness app usage or exercise behavior were found. Therefore, *Hypothesis 5* was not confirmed. Overall, body trusting not only appears to be distinct from the outcome variables, but also to other trust related variables. Therefore, it might be worth examining the role of trust in body trusting on further levels, such as item wording. When defining body trusting, the items *"I am at home in my body."*, *"I feel my body is a safe place."*, and *"I trust my body sensations."* were introduced (Mehling et al., 2012). Connecting these items with trust and trust theory, the second item is likely to represent aspects of trustworthiness (i.e., perceiving the body as trustworthy), and the third item rather reflects an intention to trust (i.e., trusting the body). The first item, however, cannot clearly be integrated into a trust concept. Therefore, the set of items used to measure body trusting makes it difficult to find a theoretical frame and to identify body trusting as an aspect of trust. Nevertheless, the item wordings used to measure body trusting imply a clear risk (or lack of risk), for example by regarding the body as safe and trustworthy. Therefore, future research should examine body trusting beyond the background of diverse body related risks to gain insight about the nature of body trusting and the role of trust within body trusting. In contrast, the items used to measure trust in technology have been established beyond the background of trust research and clearly reflect the perceived trustworthiness of a technology (McKnight et al., 2011). The incongruence across trust concepts and definitions in body trusting and trust in technology thus makes it difficult to compare body trusting and trust in technology. Furthermore, body trusting and trust in technology refer to different contexts of relevance (i.e., technology vs. the own body). Although scholars consider a general propensity to trust in terms of a stable characteristic within a person (e.g., Mayer et al., 1995; Rotter, 1980), it can be assumed that a person's propensity to trust might still vary across contexts, such as interpersonal relations, human-technology relations, and within-person relations. Still, it is yet too little known about the nature of body trusting as a potential within-person aspect of trust to make clear statements about the relations between diverse aspects of propensity to trust.

Although body trusting was found to be related with exercise behavior in Part 1 using correlations across all participants, body trusting was not related with exercise behavior in the present RSA. This might be an artefact of the sample size that was used in the analysis (i.e., full sample in Part 1 vs. people experienced in usage in Part 3). Analogue to the analysis in Part 1, trust in technology was related to fitness app usage in this analysis, whereas body trusting was not. The results again imply that trusting is related to the context of relevance.

General Discussion of Study A

Fitness apps can be a helpful device to enhance health behavior and physical activity (Schoeppe et al., 2016). However, the results of this study and other investigations (GfK, 2017b) indicate high dropout from fitness app usage. Facing potential risks associated with fitness app usage (e.g., data safety, reliability of data), trust related assumptions can be of central relevance. Thus, it was an aim of Study A to test a trust model predicting adoption and maintenance of technology on the field of fitness app usage to enhance health behavior.

Practical implications. Throughout Study A, the role of propensity to trust, institution-based trust, and trusting beliefs were investigated. First, regarding propensity to trust, the results indicate that general personal factors (i.e., propensity to trust) lead to higher levels of institution-based trust. As propensity to trust is regarded as a relatively stable and overarching individual difference, it might be of low relevance to propose interventions or structural adaptions that aim to changing a person's propensity to trust. Second, results from Part 1 imply that beliefs about data security could be of predictive value when explaining dropout from app usage. In contrast, structural assurance was not indicated to differ across users vs. non-users, but also displayed major issues regarding the scale's validity. When using fitness apps, desired app functions such as detailed profiles of a running session often require access and usage of systems that reveal highly private data. Consequently, there is a tradeoff between privacy and functionality of a fitness app. This risk is especially problematic when users are not aware of being tracked (e.g., Barcena et al., 2014; Huckvale et al., 2015). Beyond the background of multiple *objective* risks associated with fitness app usage, it has been an aim to provide guidelines for safe fitness app usage. Barcena et al. (2014) deliver recommendations for both users and app developers/service providers referring to self-tracking apps. Specifically, users on the one hand might benefit from using screen locks and strong passwords, turn off the Bluetooth function when it is not required, use software updates and full device encryption. Furthermore, users should be carefully using sharing functions and social media, avoid sharing location details, and read the privacy policy. On the other hand, app developers and service providers should build in security from the start, require strong passwords, make security testing, implement safe session management, use secure protocols, and only collect data that is required to provide a service.

Third, core findings of this study are that functionality of a fitness app is a central characteristic predicting maintenance and dropout from fitness app usage. Also, it can be assumed that high perceived reliability and helpfulness are more prevalent in users compared to non-users. Thus, it can be concluded that the facilitation of convenient tracking and data handling might be such characteristics associated with higher functionality. Lee and See (2004) emphasized that it is important to convey clear and comprehensive information about the technology's abilities and functions. Thus, the results measured by the app should be presented in a way that is easily understandable for the user, for example by simplifying the operation of the system. Also, Lee and See (2004) stressed that the purpose of the technology including its range of options, applications, and extensions should be made clear. In doing so, a user can learn about all options implemented in the app, and can evaluate how the technology fits to his or her goals. For example, a passionate runner would appreciate reliable and comprehensive measurement of his running pace, distance profile, etc. in his fitness app. In contrast, a woman exercising to regulate her body shape would appreciate a function that reliably calculates the calorie consumption and provides a function such as a large data basis including nutritional values of food, etc. This point makes clear that the *perceived functionality* stays an attribute that is highly specific to the individual and the situation.

Contextual factors. Similarly, Lee and See (2004) underlined that contextual factors (as depicted in their model of trust in automation, see Chapter 3) need to be considered when targeting the improvement of fitness app usage. The authors suggested that concrete user training and communication can ensure correct understanding and usage of the technology. In this context, cultural differences can be of importance as people from diverse cultures could differ in their expectations and experience with the technology. The contextual factors also need to be considered in terms of how the technology works context specific. Thus, it can be important to stress how the technology's performance is influenced by situations. In the context of fitness apps, it might be beneficial to outline differences in gadgets (e.g., does a step count that is implemented in a smartphone measure with the same reliability as a wearable wristband?). Even within one gadget, it can be of high importance to know about differences in measurement. For example, previous research has indicated that step count functions in wearables can provide stable and reliable data, whereas the assessment and estimation of calorie consumption can underlie high fluctuations, and therefore are considerably less reliable (Evenson, Goto, & Furberg, 2015; Kaewkannate & Kim, 2016). Thus, in sum, Lee and See (2004) advised to inform users about the technology's expected specific reliability and functionality, which would enhance helpfulness at the same time.

Strengths and limitations. Fitness apps can be a useful and low threshold technology to promote physical activity in a broad population. Study A provided insights into the determinants of adoption and maintenance of, and dropout from fitness app usage. It was a strength of this study to conduct differentiated analysis across different stages of usage and subgroups (users, non-users, and dropout) that led to a better understanding of initiation, maintenance, and dropout from fitness app usage. Furthermore, it was a strength of this study that three complimentary methodologies were used that shed differentiated light on the process of initiation, maintenance, and dropout of fitness app usage, and made it possible to better understand more complex associations and processes via sophisticated analyses. However, the different analyses yielded different, and sometimes even contradictory results referring to the contribution of the aspects of trusting beliefs. On the one hand, these results can indicate that it is of high importance to use multifaceted methodologies to elaborate on potentially more complex underlying processes. On the other hand, the results indicate that the results found in this study are of preliminary nature, and that future studies (e.g., using longitudinal designs) are needed to fully understand these underlying processes.

With the aim to understand both fitness app usage and the connected exercise behavior, trusting beliefs in fitness apps were only found to be associated with fitness app usage, but not with exercise behavior in fitness app users. However, fitness app usage and exercise behavior are two highly interrelated aspects as fitness apps are used to enhance exercise behavior. Thus, future studies are needed to elaborate on the predictors that can serve to understand both fitness app usage and the exercise behavior related to fitness app usage. As indicated in Part 1 of Study A, one such predictor that is worth being investigated in future studies might be a user's motivation.

With regards to the specific results found in this study, it was indicated that perceived functionality of a fitness app is a central aspect associated with maintenance of fitness app usage. Yet, few studies have targeted the predictive value of specific fitness app functions (e.g., Lee & Cho, 2016). Therefore, further research is needed to identify app functions leading to maintenance of app usage. Furthermore, the results found in Part 3 indicate that the frequency of fitness app usage is unrelated to trusting beliefs. In this context, it might be of interest to investigate the relationship between trusting beliefs and the frequency of trust related behavior in other contexts, such as organizational and information technology contexts.

Overall, Study A provided a comprehensive analysis of factors associated with fitness app usage, identifying trust in technology as a key aspect. Furthermore, this study provided insights into the determinants of adoption and maintenance of, and dropout from fitness app usage by applying differentiated analysis across different subgroups (users, non-users, and dropout). The following Study B will extend the knowledge about the influencing factor of trust in technology on fitness app usage by also considering the aspects of perceived benefit and risks that are associated with fitness app usage.

Study B

Digitalization and fitness app usage come with both new *risks* and *benefits* (e.g., Barcena et al., 2014; Crawford et al., 2015). For example, it has been shown that fitness apps can be useful tools to enhance physical activity and health (e.g., Schoeppe et al., 2016). However, large parts of fitness app users cease from fitness app usage (GfK, 2017). Potential risks can relate to privacy concerns and data misuse (e.g., Barcena et al., 2014), and systematic biases in data tracking and estimation can pose risks to the users' health (e.g., Kaewkannate & Kim, 2016). Beyond the background of multiple risks that are connected with fitness app usage, trust in the technology of fitness apps had been identified as a key element in predicting fitness app usage in Study A.

At the same time, the progress in media and digital communication changes rapidly, providing small starting points of experience and knowledge (e.g., Rosa & Scheuermann, 2010). Especially when the perceived trustworthiness of a trustee is based on little or no personal experience during early stages of trustor-trustee relationships, initial trust is present (Lewicki & Bunker, 1996; McKnight et al., 2011). The formation of initial trusting intentions and behavior are mainly guided by the assessment of costs and benefits (Lewicki & Bunker, 1996). Therefore, when examining initial trust in digital environments, the risk vs. benefit assessment is a crucial factor to consider. One widely accepted theory to explain technology related intentions and behavior on the basis of perceived benefit (i.e., perceived usefulness), is the Technology Acceptance Model (TAM; Davis, 1989; Davis et al., 1989). In the field of e-commerce, Kim et al. (2008) identified a model that is based on trust research and the TAM model to explain how trust, diverse dimensions of perceived risk and benefit affect the intention to purchase and purchasing behavior in persons experienced in e-commerce (Figure 58).

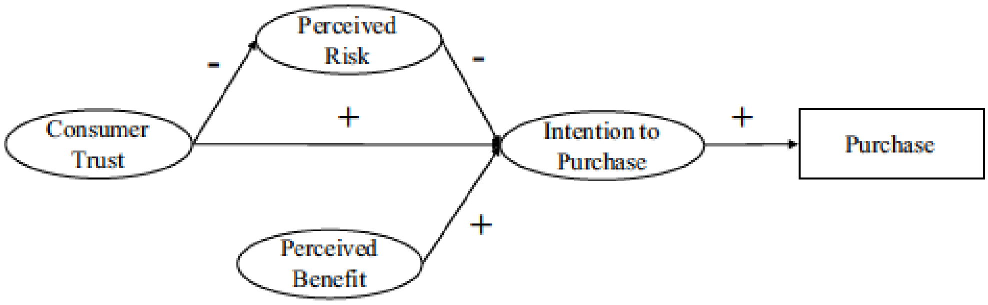


Figure 58. Model of trust, perceived risk and benefit in e-commerce, adapted from Kim et al. (2008).
Note: +, positive association; -, negative association.

Specifically, Kim et al. (2008) referred to the trust concept established by Mayer et al. (1995) to measure trustworthiness. To assess perceived risk, Kim et al. (2008) applied Jacoby and Kaplan's (1972) concept of dimensional risk, utilizing a combination of items that had been used in previous studies (Gefen, 2000; Jarvenpaa et al., 2000), and items created by the authors. Similarly, a mix of items that had been used in previous studies and self-created items served to measure perceived benefit. In their study, Kim et al. (2008) conducted structural equation modelling (SEM), explaining how trust, perceived risk, and benefit affect (1) the intention to purchase and (2) purchasing behavior in persons that were experienced in e-commerce. As presented in Figure 58, intention to purchase was negatively affected by perceived risk, and was positively affected by trust and perceived benefit. Furthermore, trust negatively affected perceived risk, indicating that perceived risk can be regarded as a mediator variable. In the SEM, a good model fit indicated validity for the proposed model, suggesting a mediating role of perceived risk between trust and intention to purchase.

However, the interrelations between trust, perceived risk, and perceived benefit have not yet been examined in the field of technology applications, such as fitness app usage. Therefore, Study B was designed to apply the model introduced by Kim et al. (2008) in the field of fitness app usage. As risk and benefit have been identified as dimension specific and specific to the context, it was an aim to provide a differentiated analysis of each dimension. Therefore, different versions of solutions were calculated: (1) a latent solution with all dimensions loading on a latent factor of each risk and benefit; (2) dimension specific solutions with the risk/benefit dimension defined as a manifest variable. Following previous research that had successfully combined trust theories and the TAM in technology (specifically, e-commerce) context (Gefen et al., 2003; Kim et al., 2008), this study was the first to test a model including aspects of trust, benefits, and risks in the field of fitness app usage (Figure 59).

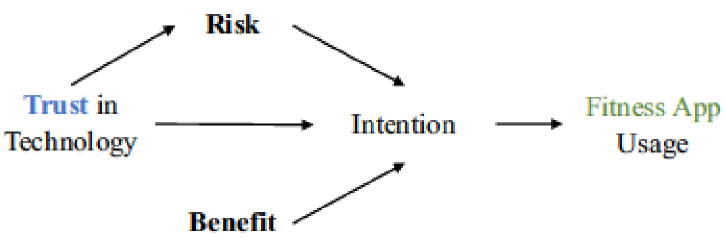


Figure 59. Visualization of the specific research question based on the model proposed by Kim et al. (2008) and the relations between the variables tested in Study B.

Overall, Study B contributes to the understanding of relations between fitness app usage, trust in technology, and the specific role of risks and benefits with regards to the research framework model introduced in this work[2].

Hypotheses. It was hypothesized that the relations between trust, perceived risk, perceived benefit, intention to use, and trusting behavior as illustrated by the trust-based consumer decision-making model in e-commerce (Kim et al., 2008) can be applied to the context of fitness app usage (Figure 59).

[2] The development of the research design was supported by Anja Schmitt, Till Utesch and Bernd Strauss.

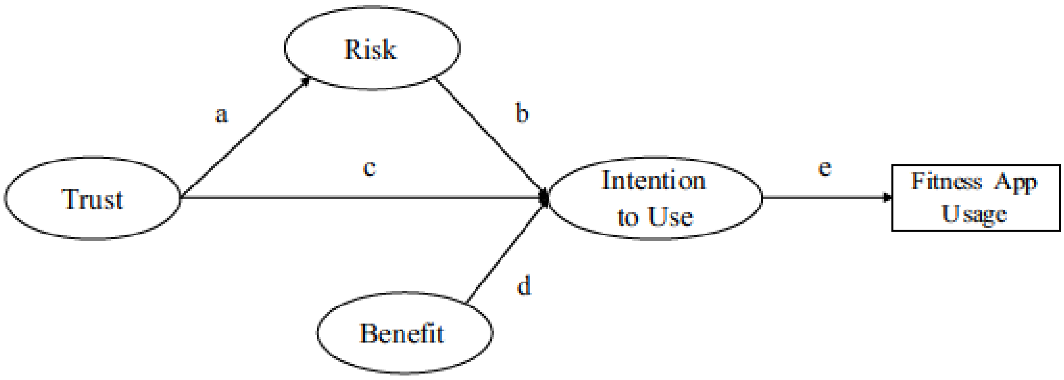


Figure 60. Visualization of the model tested in Study B.
Note: The paths between the variables are labelled "*a*" to "*e*" for reasons of identifiability.

Specifically, it was hypothesized:

Hypothesis 1: Trust is positively associated with the intention to use a fitness app (Figure 60, path *c*).

Hypothesis 2: The intention to use a fitness app is positively associated with fitness app usage (Figure 60, path *e*).

Hypothesis 3: Trust is negatively associated with perceived risk (Figure 60, path *a*).

Hypothesis 4: Perceived risk is negatively associated with the intention to use a fitness app (Figure 60, path *b*).

Hypothesis 5: Perceived benefit is positively associated with the intention to use a fitness app (Figure 60, path *d*).

Methods

Participants and procedures. A total of N = 388 adults between 18 and 58 years (M_{age} = 25.94, SD_{age} = 7.08; Mdn_{age} = 24; 74.13% female) were recruited via flyers with printed online links that were distributed at the University of Münster, recreational areas, and sport clubs. The questionnaire was provided via the online survey program *unipark* (Questback GmbH, 2018). The online link was accessible from 25th April 2018 to 24th July 2018. Participants completing all questionnaires could win one out of ten 10 € gift cards. Winners were informed and paid after the end of the data collection. The online questionnaire was programmed to make it impossible to skip questions, and no participant was excluded from filling in the questionnaire. Prior to the data collection, the study was approved by the ethics committee of the University of Münster. An a priori estimation of the required sample size was conducted via an online tool that provides sample size calculations for structural equation models (Soper, 2012). The anticipated size of each coefficient was based on the model provided by Kim et al. (2008). Defining a desired statistical power level of .80, a probability level of α = .05, a number of five latent variables and 26 observed variables in the model with latent risk and benefit variables, it was estimated that a minimum sample size for the model structure was n = 113, and that a minimum sample size to detect a small effect of .30 was n = 150. In this study, only fitness app users and those who had dropped out were of interest for the analysis of trusting beliefs, as trusting beliefs in the technology of fitness apps are recognized as constructs that can be measured validly during post-adoption. Based on previous studies (GfK, 2017) it was estimated that 50% of the recruited sample had used a fitness app before. In sum, data sets of N = 213 participants were included in the analysis.

Measures. The reliability of each subscale used in the present study was tested for the present sample using the following procedure: First, it was tested whether the congeneric or the essential τ-equivalent (equal loadings) unidimensional factor model fits the subscale better. Cronbach's α was used to estimate subscale reliability for essential τ-equivalent measurement models. Mc Donald's ω_H was conducted for congeneric models, because Cronbach's α tends to overestimate coefficients for congeneric data (Zinbarg et al., 2005). To facilitate comparisons with other studies, Cronbach's α coefficients are presented additionally, but should not be interpreted in case the congeneric model fits the data better compared to an essentially τ-equivalent model.

Trust in fitness apps. A German version of the trust in a specific technology questionnaire (McKnight et al., 2011) adapted to the context of fitness apps that was introduced in Study A was distributed. In this study, the functionality scale (3 items that are rated on a 7-point Likert scale, ranging from 1 = *not agree* to 7 = *fully agree*) was used. All items are presented in Table 15. The functionality scale of the trust in fitness apps questionnaire was used to measure trust, because functionality beliefs were associated with duration of fitness app usage in Study A, whereas reliability and helpfulness were not. Because a congeneric model fitted the data better compared to an essentially τ-equivalent model in this study ($\Delta\chi^2$ = 8.89, df = 2, p = .012), ω_H should be interpreted. Reliability was ω_H = .81 (α = .80).

Perceived risk. Perceived risk of fitness app usage was assessed via six items based on the questionnaire provided by Jacoby and Kaplan (1972). The six items representing the dimensions of risk were adapted to the fitness app context and were rated on a 9-point Likert scale ranging from 1 = *very low* to 9 = *very high*. The dimensions of risk were financial risk (losing money), performance risk (the app would not work as expected), physical risk (health related issues), psychological risk (incompatibility with the self-concept), social risk (how usage would affect what people think of someone), and overall perceived risk. The congeneric model fitted the data better than an essentially τ-equivalent model in this study ($\Delta\chi^2$ = 26.75, *df* = 5, $p < .001$), and therefore ω_H should be interpreted. Reliability of the questionnaire was $\omega_H = .74$ ($\alpha = .73$).

Perceived benefit. Considering risk and benefit as related constructs, the questionnaire provided by Jacoby and Kaplan (1972) that measures the perceived risk on six dimensions was reworded. Thus, the participants were asked to rate the perceived benefit on a 9-point Likert scale ranging from 1 = *very low* to 9 = *very high*. The aspects of benefit were financial benefit (gain money), performance benefit (the app works as expected), physical benefit (health related aspects), psychological benefit (compatibility with the self-concept), social benefit (how usage affects what people think of someone), and overall perceived benefit. The congeneric model fitted the data better than an essentially τ-equivalent model in this study ($\Delta\chi^2 = 71.04$, *df* = 5, $p < .001$), and therefore ω_H should be interpreted. Reliability of the questionnaire was $\omega_H = .80$ ($\alpha = .78$).

Intention to use. To assess the intention to use a fitness app, the two-item questionnaire provided by Ajzen and Driver (1992) to measure intentions in the Theory of Planned Behavior was applied and rated on a 7-point Likert scale. The two items were adapted to the fitness app usage context: "*I plan to use a fitness app in the next six months*" ranging from 1 = *not at all* to 7 = *frequently*, and "*I will try to use a fitness app in the next 6 months*" ranging from 1 = *not at all* to 7 = *very much*. In the case of scales entailing only two items, reliability represents the simple correlation between the items. Therefore, both ω_H and α yield the same coefficients. Reliability of the questionnaire was $\omega_H = .95$ ($\alpha =$ .95).

Fitness app users and duration of fitness app usage. Trusting beliefs are considered as a concept that can be observed when a trustor has gained experience with the trustee or technology (Mayer et al., 1995; McKnight et al., 2011). Thus, measurement of trusting beliefs can be valid in persons who have used the technology in the past (i.e., in users and dropout).

Consequently, fitness app users and dropout were considered for the analysis in this study, whereas non-users were not. The participants were asked whether they (1) were currently using a fitness app (*users*); (2) had used a fitness app in the past (*dropout*); or (3) had never used a fitness app before (*non-users*). $n = 133$ participants (34.28% of the total sample) were identified as *users*, and $n = 22$ participants (31.44% of the total sample) were identified as *dropout*. In sum, $N = 213$ completed questionnaires could be used for the analysis.

To assess the duration of fitness app usage, fitness app users and dropout were asked: "*For how many weeks have you used a fitness app in the past?*" and to give their answer in weeks. One participant was identified with an extreme outlier (i.e., 43224 weeks) and was excluded from the analysis. Participants stated to have used a fitness app for a mean duration of 46.63 weeks ($SD = 62.41$), ranging from 0 to 320 weeks.

Statistical Analyses

For the analysis of correlations between trusting beliefs in fitness-apps, perceived risk, perceived benefit, intention to use, and fitness app usage, bivariate Pearson correlation coefficients were calculated and interpreted as small ($.10 \leq r \leq .30$), medium ($.30 \leq r \leq .50$), or large ($.50 \leq r \leq .80$) based on Cohen's (1992) recommendations. To test the hypotheses, a SEM was conducted. Multivariate distribution of the variables was analyzed via tests for normality, skewness, and kurtosis (Mardia, 1985). The coefficients indicated absence of multivariate normality ($\chi^2 = 1913.46$ for skewness, $p < .001$; and $z = 37.29$ for kurtosis, $p < .001$). Thus, the scaled estimator *MLR* with robust standard errors and a scaled test statistic was used in the SEM. Missing values were handled using the full information maximum likelihood *fiml*. Evaluation of the model fit was conducted on the basis of criteria suggested by Hu and Bentler (1999; CFI and TLI $\geq .95$; RMSEA $\leq .06$; SRMR $\leq .08$). At the measurement model level of the SEM, the latent variables trust, perceived risk, perceived benefit, intention to use, and the manifest variable duration of fitness app usage were entered.

To investigate the risk and benefit dimension specific associations, six domain specific measurement models with risk and trust dimensions defined as manifest variables and represented by their mean values were conducted (Table 16). The contribution of each risk and benefit dimension to overall perceived risk and benefit can be identified via the factor loadings of the latent model.

All statistical analyses were conducted with the *System for Statistical Computation and Graphics R* (R Core Team, 2018) using the packages *lavaan* (Rosseel, 2012) and *semTools* (semTools Contributors, 2016). Mardia tests for normality, skewness, and kurtosis were applied via the package *mvn* (Korkmaz et al., 2014). The full *R* code of the analysis, the original data, and open material such as the codebook including all items are provided in a supplementary file on https://osf.io/b2yrg/?view_only=aadac4c2e1ec43c780ef2fce3ce75901.

Table 15

Items, Item Codes, and English Translation of the Item Wording Used in this Study

Construct	**Item Code**	**Item Content**	**Item Wording (English translation)**
Intention to Use			
	ITU_App1	Intention to use	*I plan to use a fitness app in the next six months*
	ITU_App2	Intention to use	*I will try to use a fitness app in the next 6 months*
Fitness App Usage	Fitness App Usage	Duration of fitness app usage	*For how many weeks have you used a fitness app in the past?*
Trust			
	Ver_Funk1	Functionality scale	*This app has the functionality I need.*
	Ver_Funk2	Functionality scale	*This app has the features required for my tasks.*
	Ver_Funk3	Functionality scale	*This app has the ability to do what I want it to do.*
Perceived Risk			
	Risk_App_Fin	Financial risk	*What are the chances that use of a fitness app will cause financial losses for you?*
	Risk_App_Perf	Performance risk	*What is the likelihood that a fitness app will not work properly?*
	Risk_App_Phys	Physiological risk	*What are the chances that the use of a fitness app will endanger your health?*

	Risk_App_Psych	Psychological risk	*What are the chances that the use of a fitness app will not match your self-concept (i.e., the way that you think about yourself)?*
	Risk_App_Soc	Social risk	*What are the chances that the use of a fitness app will negatively affect the way others think of you?*
	Risk_App_Total	Overall risk	*On the whole, considering all sorts of factors combined, how risky would you say is to use a fitness app?*
<u>Perceived Benefit</u>			
	Use_App_Fin	Financial benefit	*What are the chances that use of a fitness app will cause financial gains for you?*
	Use_App_Perf	Performance benefit	*What is the likelihood that a fitness app will work properly?*
	Use_App_Phys	Physiological benefit	*What are the chances that the use of a fitness app will be beneficial for your health?*
	Use_App_Psych	Psychological benefit	*What are the chances that the use of a fitness app will match your self-concept (i.e., the way that you think about yourself)?*
	Use_App_Soc	Social benefit	*What are the chances that the use of a fitness app will positively affect the way others think of you?*
	Use_App_Total	Overall benefit	*On the whole, considering all sorts of factors combined, how beneficial would you say is to use a fitness app?*

Table 16

Structural Equation Model Specifications

	Element in the Structural Equation Model				
	Trust	**ITU**	**App Usage**	**Risk**	**Benefit**
Risk and Benefit Dimensions					
1. Latent Model	Latent (4 items)	Latent (2 items)	Manifest	Latent (6 items)	Latent (6 items)
2. Financial	Latent (4 items)	Latent (2 items)	Manifest	Manifest (financial risk)	Manifest (financial benefit)
3. Performance	Latent (4 items)	Latent (2 items)	Manifest	Manifest (performance risk)	Manifest (performance benefit)
4. Physiological	Latent (4 items)	Latent (2 items)	Manifest	Manifest (psychological risk)	Manifest (psychological benefit)
5. Psychological	Latent (4 items)	Latent (2 items)	Manifest	Manifest (psychological risk)	Manifest (psychological benefit)
6. Social	Latent (4 items)	Latent (2 items)	Manifest	Manifest (social risk)	Manifest (social benefit)
7. Overall	Latent (4 items)	Latent (2 items)	Manifest	Manifest (total risk)	Manifest (total benefit)

Table 17

Item Characteristics of All Scales Assessed in this Study

	Range	*M*	*SD*	*SE*	Skewness	Kurtosis	ω_H	α
Trust (3 items)	1–7	4.53	1.20	0.09	–0.69	0.42	.81	.80
Risk (6 items)	1–9	3.30	1.18	0.09	0.41	–0.38	.74	.73
Benefit (6 items)	1–9	5.06	1.22	0.09	–0.33	0.16	.80	.78
Intention to use (2 items)	1–7	4.25	2.00	0.14	–0.16	–1.33	.95	.95
Fitness app usage (in weeks)	0–320	46.63	62.41	4.28	2.11	4.60	-	-

Note. In order to facilitate interpretation of reliability coefficients, α is reported in addition to ω_H.

Table 18

Correlation Matrix (N = 235)

	App Usage	Trust	ITU	Overall Risk	Overall Benefit	Fin. Risk	Perf. Risk	Physiol. Risk	Psychol. Risk	Social Risk	Fin. Benefit	Perf. Benefit	Physiol. Benefit	Psychol. Benefit
App Usage	–													
Trust	.16	–												
ITU	.41	.46	–											
Overall Risk	–.23	–.22	–.21	–										
Overall Benefit	.30	.50	.52	–.32	–									
Financial Risk	–.16	–.19	–.15	.38	–.17	–								
Perf. Risk	–.11	–.31	–.21	.17	–.27	.05	–							
Physiol. Risk	–.08	–.10	–.10	.51	–.13	.24	.14	–						
Psychol. Risk	–.25	–.18	–.29	.50	–.28	.27	.29	.37	–					
Social Risk	–.08	–.10	–.05	.50	–.21	.21	.14	.27	.45	–				
Financial Benefit	–.06	.02	.01	.21	.05	.17	–.10	.22	.13	.12	–			
Perf. Benefit	.16	.47	.32	–.20	.60	–.27	–.17	–.09	–.19	–.12	.07	–		
Physiol. Benefit	.09	.50	.29	–.20	.58	–.20	–.30	–.19	–.22	–.15	.04	–.19	–	
Psychol. Benefit	.32	.31	.38	–.19	.66	–.27	–.17	–.11	–.46	–.17	.05	–.27	.44	–
Social Benefit	.06	.17	.20	–.27	.43	–.08	–.15	–.02	–.14	.11	.11	–.12	.31	.47

Note. ITU, Intention to use; Perf. Risk/Benefit, Performance Risk/Benefit; Physiol. Risk/Benefit, Physiological Risk/Benefit; Psychol. Risk/Benefit, Psychological Risk/Benefit.

Results

The scale characteristics and reliability coefficients of the assessed variables are presented in Table 17. Means of trust (M = 4.53, SD = 1.20) and intention to use (M = 4.25, SD = 2.00) were medium high (both ranging on a 7-point scale) as well as the mean of perceived benefit (M = 5.06, SD = 1.22), ranging on a 9-point scale. The mean of perceived risk was low (M = 3.30, SD = 1.18), ranging on a 9-point scale.

With regards to the bivariate correlations (see Table 18), the dimensions of risk and benefit were associated with trust, intention to use, and fitness app usage to different degrees, depending on the risk and benefit dimension. The risk dimensions were negatively associated with trust, intention to use, and fitness app usage ($-.08 \leq r \leq -.29$). The benefit dimensions were mostly positively associated with trust, intention to use, and fitness app usage ($-.06 \leq r \leq .50$). Intention to use was associated with fitness app usage (r = .41) and trust (r = .46) to a medium extent. Trust was associated with fitness app usage to a small degree (r = .16).

When analyzing the SEM with risk and benefit defined on a latent level (Figure 61), an insufficient model fit was found (N = 213, χ^2 = 283.46, df = 130, $p < .001$; CFI = .88; TLI = .85; RMSEA = .083 [.070; .096]; SRMR = .096). Explained variance was R^2 = .34 in intention to use and R^2 = .19 in fitness app usage. Good model fits were identified in the risk and benefit dimension specific models specified for the financial (N = 213, χ^2 = 20.42, df = 18, p = .310; CFI = .99; TLI = .99; RMSEA = .029 [.000; .080]; SRMR = .040) and social (N = 213, χ^2 = 25.75, df = 18, p = .106; CFI = .98; TLI = .98; RMSEA = .053 [.000; .095]; SRMR = .054) dimensions. In these models, trust was unrelated to risk, and benefit was unrelated to intention to use (paths a and d, Table 19).

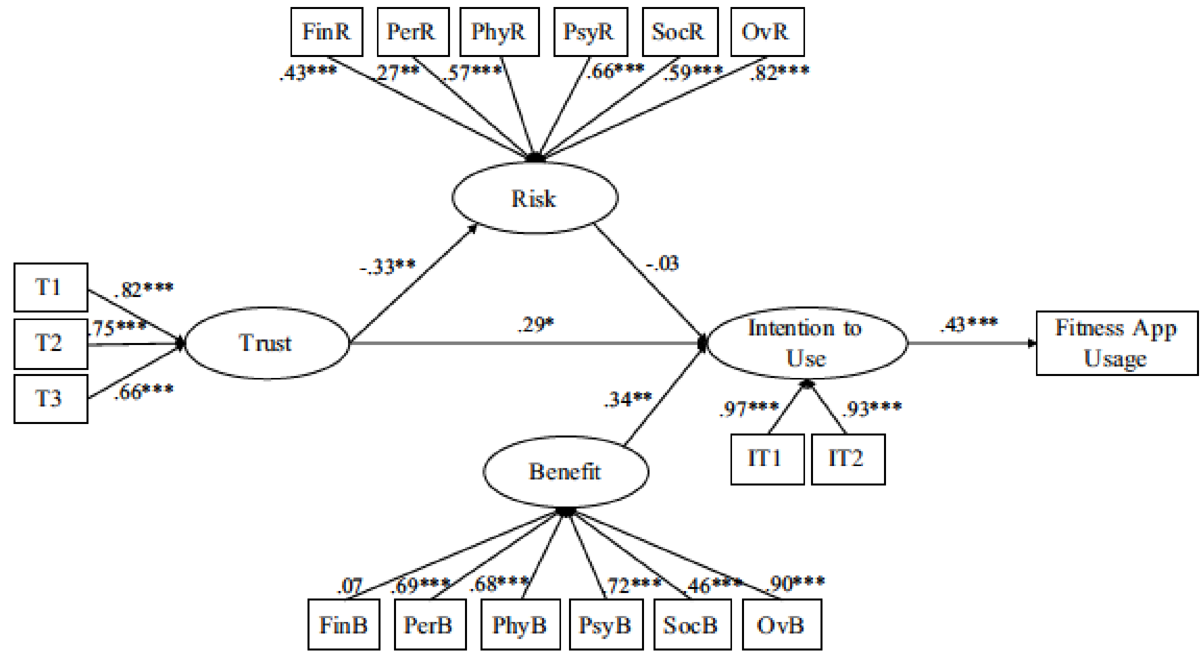


Figure 61. Results of the model with risk and benefit as latent factors.
Note: For a description of the item labels, see Table 15.

Across all seven solutions, trust was significantly associated with intention to use (.29 $\leq \beta \leq$ .50; path *c*), and intention to use was significantly associated with fitness app usage (.41 $\leq \beta \leq$ .43; path *e*). Also, risk was not significantly associated with intention to use (–.06 $\leq \beta \leq$ –.02; path *b*) across all solutions. The degree and significance of the associations between trust and risk (–.34 $\leq \beta \leq$ –.08; path *a*) and between benefit and intention to use (–.00 $\leq \beta \leq$ .41; path *d*) were dimension specific. When analyzing the financial, psychological, and social dimensions, no associations between trust and risk and benefit and intention to use were found. In the model defining risk and trust on a latent level, and in the performance, psychological and overall benefit and risk models, significant associations between trust and risk, and benefit and intention to use were found (Table 19).

Table 19

Structural Equation Model Results of the Models Incorporating the Risk and Benefit Dimensions (N = 213)

	Path Estimates					Model Fit							
	a	**b**	**c**	**d**	**e**	χ^2	*df*	*p*	**CFI**	**TLI**	**RMSEA**	**95%-CI**	**SRMR**
Dimensions													
1. Latent Model	–.33**	–.03	.29*	.34**	.43***	283.58	130	< .001	.88	.86	.076	[.064;.088]	.092
2. Financial	–.19	–.06	.50***	–.00	.43***	20.42	18	.310	.99	.99	.029	[.000;.080]	.040
3. Performance	–.34***	–.03	.44***	.17*	.42***	59.84	18	< .001	.92	.87	.125	[.091;.161]	.119
4. Physiological	–.08	–.05	.48***	.07	.42***	88.52	18	< .001	.87	.80	.155	[.124;.188]	.131
5. Psychological	–.17*	–.13	.44***	.23**	.42***	71.57	18	< .001	.90	.85	.138	[.105;.172]	.119
6. Social	–.08	–.02	.49***	.14	.43***	25.75	18	.106	.98	.98	.053	[.000;.095]	.054
7. Overall	–.23**	–.02	.32**	.41***	.41***	90.25	18	< .001	.88	.82	.152	[.122;.184]	.147

Note. a = path from Trust to Risk, b = path from Risk to Intention to Use, c = path from Trust to Intention to Use, d = path from Benefit to Intention to Use, e = path from Intention to Use to Fitness App Usage; see Figure 60.

Discussion

Fitness apps can be helpful devices to enhance the practice of health behavior and physical activity (Schoeppe et al., 2016). However, high dropout rates from fitness app usage are observed (GfK, 2017). Facing potential risks and benefits associated with fitness app usage (e.g., reliability of data, performance benefits), trust related assumptions can be of central relevance. Therefore, it was an aim of this study to apply a trust model that integrates perceived risk and benefit to explain trusting intentions and trusting behavior (Kim et al., 2008) and to test it on the field of fitness app usage.

Trust, intentions, and fitness app usage. It was hypothesized that trust is positively associated with the intention to use a fitness app. In this study, trust in the functionality of a fitness app was identified as a consistent predictor of the intention to use across all models. Thus, *Hypothesis 1* was confirmed, indicating that trusting beliefs in a fitness app are of considerable relevance in a person's intention to use a fitness app. Across studies conducted in the field of trust research and technology usage, trusting beliefs have been identified as an important antecedent of trusting intentions and trusting behavior (e.g., Kim et al., 2008; McEvily & Tortoriello, 2011; McKnight et al., 2011). For example, Gill et al. (2005) found ability, benevolence, and integrity to be predictors of trusting intentions in an experimental design, and McKnight et al. (2011) identified reliability, functionality, and help function as predictors of the intention to use a technology. However, only functionality beliefs were found to predict fitness app usage in Study A, whereas reliability and helpfulness displayed mixed evidence.

Furthermore, it was hypothesized that the intention to use a fitness app is positively associated with fitness app usage. In this study, the intention to use was associated with fitness app usage. Consequently, intentions were found to be an important factor to explain decisions of maintenance or dropout from fitness app usage, confirming *Hypothesis 2*. Behavioral intentions have been consistently found to predict actual behaviors across studies conducted in trust research and technology usage (e.g., within the TRA and TAM; Davis et al., 1989; Mayer et al., 1995; Söllner et al., 2012). Across different studies and contexts, intentions have been identified as important drivers of general and health related behavior (Ajzen & Driver, 1992; Hagger, Chatzisarantis, & Biddle, 2002; Hausenblas, Carron, & Mack, 1997). Thus, scholars of trust research have consistently integrated an intentional component in their conceptualizations of the relations between trusting beliefs and trusting behavior (e.g., McEvily & Tortoriello, 2011; McKnight, 1998). Accordingly, the associations between trust, intention to use, and fitness app usage were in line with the results found in Kim et al.'s (2008) study. The results of this study indicate that trusting intentions are of relevance in the connection between trusting beliefs and trusting behavior and should be considered in theory building and practical applications.

Perceived risk. Risk has been identified as a dimensional concept (Jacoby & Kaplan, 1972). Also, the importance of each dimension is considered specific to the context and situation. In this study, six risk and benefit dimensions were considered for a differentiated investigation of the dimension specific effects on trusting intentions. In a model defining risk and benefit as latent variables and integrating the dimensions of risk and benefit dimensions altogether, a non-sufficient model fit was found (Table 19). Thus, the results found in this study underline that the different risk dimensions need to be targeted in separate analyses and that dimensions of risk need to be targeted separately. To test the individual contribution of each dimension on total perceived risk, Jacoby and Kaplan (1972) conducted multiple regressions. In this study, the contributions of each risk and benefit dimension can be observed in the factor loadings of the latent model (Figure 61). The results indicate that in the context of fitness app usage, physiological, psychological, and social risks, and performance, physiological, and psychological benefit are the most relevant risk and benefit dimensions.

Based on the results found in Kim et al.'s (2008) study, it was hypothesized that trust would be negatively associated with risk, and risk would be associated negatively with the intention to use. In this study, trusting beliefs were associated with lower levels of perceived risk in the performance, psychological, and overall models. Therefore, *Hypothesis 3* was partly confirmed. Trust was operationalized as the perceived functionality of a technology, representing beliefs about good performance of a technology (McKnight et al., 2011). Therefore, it seems consequential that trust had the strongest negative effect on perceived risk in the performance specific model. That is, if persons trust the functionality of a fitness app, they perceive a smaller risk that the app might perform poorly. Overall, the results found in this study indicate that trusting beliefs can contribute to the reduction of perceived risks, however limited to specific dimensions. The results are in line with research postulating that trust serves as a mechanism to reduce perceived risks (e.g., Das & Teng, 2004; Lewicki et al., 2006), but contradicts the model postulated by Mayer et al. (1995), assuming that trust has no influence on perceived risk.

With regards to the connection between risk and intention to use, risk was not associated with the intention to use a fitness app across all solutions (path *b*, Figure 60). Therefore, *Hypothesis 4* was not confirmed in this study. Perceived risks appear to be of minor relevance in the overall decision-making process of fitness app usage. Across scholars, trust has been defined as a mechanism that reduces the risk perception, mediating the relationship between trust and trusting intentions (Das & Teng, 2001; Lewicki et al., 2006; Kunnel, 2017; Kim et al., 2008). Hence, if persons trust the other party, they perceive a smaller risk to face negative outcomes, and therefore are more likely to interact with the other party. This latter relationship has been considered and tested in many studies in the online communication context (Kim et al., 2008; Jarvenpaa et al., 2000; Mitchell, 1999; Pavlou, 2003), mobile banking (Luo et al., 2010), or social media platforms (Wang et al., 2015). Bradach and Eccles (1989, p. 104) stress the positive expectation (i.e., perceived benefit) towards the other party, defining trust as "a type of expectation that alleviates the fear that one's exchange partner will act opportunistically". From this point of view, the trustor is aware of potential risks in interactions, but changes his or her evaluation (e.g., as dangerous) in the relationship with a trustworthy party. Align with these findings, low mean values were found on the risk scales in this study. These results indicate that the perceived risk of fitness app usage might be generally low in persons who are experienced in fitness app usage. Jacoby and Kaplan (1972) indicated that the overall perceived risk of expensive products is considerably higher compared to the perceived risk for low-price products. These findings might explain the low perceived risk of fitness app usage found in this study as fitness apps are either free of charge or of little cost. In sum, the results imply that trust in fitness apps can be regarded as a mechanism to reduce perceived risk and thus lead to a lower (or even non-identifiable) relationship between perceived risk and the intention to use a fitness app. However, longitudinal studies are needed to fully understand the relations between trustworthiness, perceived risk, and trusting intentions.

Perceived benefit. Fitness apps can provide many useful features to improve physical performance (West et al., 2012). It was hypothesized that perceived benefits are positively associated with the intention to use a fitness app. When analyzing the associations between benefit and the intention to use (path *d*, Figure 60), a domain specific pattern was found in this study. Specifically, benefits of good app performance (i.e. app functions and reliable data recording) and perceived psychological benefits were positively associated with the intentions to use. Therefore, *Hypothesis 5* was partly confirmed. Psychological benefits represent the perception of how the fitness app is compatible with the self-concept and how a person identifies with a fitness app related lifestyle (e.g., being sportive and health-conscious). With regards to performance benefits of fitness apps, Yuan et al. (2015) found that high levels of performance expectancy were the strongest predictor of the intention to continue fitness app usage in their study. In further studies, it was identified that the most important app features for people were the possibility to easily record and document behavior and to receive advice and information (Dennison et al., 2013; Salzwedel et al., 2017).

Overall, good model fits were identified in the financial and social dimension specific models in this study. In both models, perceived benefits and risks were unrelated to the intention to use a fitness app. These results indicate that potential financial benefits (which may be unlikely in the context of fitness app usage) do not influence the intention to use a fitness app. With regards to social risks and benefits, potential social benefits, such as gains in social reputation, might be of minor relevance in the intention formation to use a fitness app. However, in contrast, Lee and Cho (2016) identified the possibility to interact with other users (i.e., social benefit) as a predictor of fitness app usage. The differences might be due to wording effects, for example indicating that the item wording used to measure social benefit in this study might have been too unspecific. Furthermore, perceived physiological risk and benefit were unrelated to the intention to use a fitness app in this study. These results indicate that people experienced in fitness app usage are unlikely to consider potential health benefits in their intention to use a fitness app. However, in studies investigating the health-related outcomes of fitness app usage it was found that the risk of inactivity and resulting problems can be reduced (Higgins, 2016; West et al., 2012; Schoeppe et al., 2016), and that the motivation to stay healthy is one of the major reasons to use a fitness app (GfK, 2017). In sum, various heterogenous results were found across studies targeting the risks and benefits of fitness app usage. Therefore, the need is raised to elaborate on this aspect in future studies.

Limitations and further research. In this study, trust related predictors of the intention to use a fitness app were analyzed. The duration of fitness app usage was assumed to be guided by behavioral intentions and trust related aspects. Therefore, the mediating role of intentions between trusting beliefs and behavior seem to be of central relevance, especially when comparing the conceptual background of trust models and trust research—for example postulated by McEvily and Tortoriello (2011) and McKnight (1998)—with the results found in this study. Nonetheless, fitness app usage can also be guided by other influencing factors such as habits (Stawarz, Cox, & Blandford, 2015). Although intentions are important predictors of behavior, researchers acknowledge that there is an intention-behavior gap whereby intentions do not always translate into behavior (Armitage & Conner, 2001). Thus, it can be interesting to examine these potential factors that directly affect fitness app usage beyond the trust research context. Future studies in the general field of fitness app could target this research question.

In the original study establishing the model targeted in this study, Kim et al. (2008) used a sample of participants who were experienced in the practice of e-commerce. To assess trust in this study, a technology specific aspect of trusting beliefs was used that can be measured validly in persons who are experienced with fitness app usage (i.e., fitness app users and dropout), as indicated in Study A. However, previous research has indicated that the risk assessment during an act of trust underlies risk reduction strategies. Consequently, the perceived risk is higher during pre-experience compared to post-experience (Mitchell, 1999; Mitchell & Boustani, 1994) due to the application of risk reduction strategies. Therefore, the participants' assessment of risks and benefits was guided by previous experience and knowledge about the fitness app, which might have led to biased evaluations in fitness app users (e.g., lower levels of risks and higher levels of benefits).

In this study, the risk concept established and validated by Jacoby and Kaplan (1972) and Kaplan et al. (1974) was used, identifying five individual risk dimensions and an additional overall risk dimension. Future research might also consider other dimensions of risk that are specifically relevant to the usage of fitness apps. For example, privacy risks are often considered important when it comes to the collection of health data (Dehling et al., 2015; Dennison et al., 2013). Likewise, studies in the context of other electronic services included privacy risks as one facet of risk (Featherman & Pavlou, 2003; Luo et al., 2010; Park, 2004). However, it was identified in Study A that the perception of aspects related to privacy issues are not associated with trusting beliefs in fitness app users. Moreover, privacy risk could have been represented in the performance and overall dimensions in this study, but they were not explicitly specified.

Practical implications. Study B is a conceptual work targeting the explanation of trusting intentions and trusting behavior in fitness app usage, providing implications for both theory building and for practical applications. Advancing previous studies, domain specific dimensions of risk and trust were identified that were associated with the intention to use a fitness app in this study, i.e., performance, psychological and overall benefit. Thus, fitness app providers might benefit from targeting these aspects to potentially increase the maintenance of fitness app usage and health behavior. With respect to the psychological benefits, it might be useful to promote a pronounced variety of self-concepts that can be associated with fitness app usage. Apart from underlining the image of a sportive person, also other self-concepts such as the concepts of a technology-oriented person, a playful person, an efficient person, or a health-conscious person could be outlined. Furthermore, the overall performance of the gadget could be improved (see also Dennison et al., 2013; Salzwedel et al., 2017) and manifold functionalities could be provided that help users to fulfil their goals and that match their self-concept.

Overall, following Study A that had shed light into the process of initiation of, maintenance of, and dropout from fitness app usage using trust in technology as a key factor, Study B contributed to understanding the additional roles of perceived dimensions of benefit and perceived dimensions of risks. In the following, Study C targets a longitudinal analysis within the model of trust in technology to provide further understanding of causal processes associated with the initiation of, maintenance of, and dropout from fitness app usage. Furthermore, a novel form of trust in the context of fitness app usage is targeted, i.e., body trusting, specifically looking at the effects of self-tracking on diverse body and trust related aspects.

Study C

The results of Study A and Study B indicated that trust in the technology of fitness apps is a key element to explain fitness app usage and that specific perceived benefits (such as *psychological* benefits) can positively influence the intention to use a fitness app. People engaged in self-tracking hope to find patterns in their behavior, find causes and trajectories of a disease or of unhealthy behavior (Moschel, 2013), indicating psychological benefits of fitness app usage. Also, self-tracking via fitness apps has been described as a means to practice body awareness and body trusting (van Dijk et al., 2015; Sharon & Zandbergen, 2017), raising the matter of trust. Therefore, it is crucial to better understand the *psychological* and *trust related risks* and *benefits* that are associated with fitness app usage.

In this context, it is also interesting to understand the psychological effects of specific external goal setting (i.e., 10,000 steps per day) that are implemented in many fitness apps. First, such goals provided by the app can imply social norms or a reality that are unattainable for many fitness app users (Depper & Howe, 2017), and might convey a perception of social pressure (Lupton, 2013), posing a *risk* to psychological well-being. Second, it is of interest to examine whether external goal setting during physical activity can shift the behavioral focus away from relying on own body perceptions to a desire to attain external cues, and therefore undermine body listening and body trusting.

Specifically, it is unclear how and if continuous self-monitoring of one's own physical activity level influences the effects on self-reported capability to listen to body states, and how specific goal setting (i.e., 10,000 steps per day) is related to body listening, body trusting, and psychological well-being. In addition, it is not yet understood whether trust in the technology of fitness apps can mediate this relationship and how body trusting is related to psychological well-being (Figure 62).

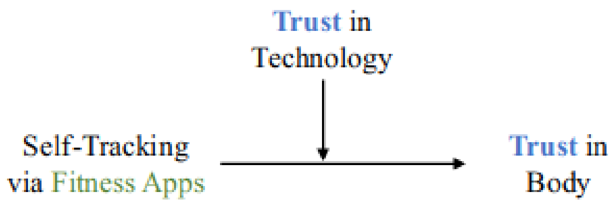


Figure 62. Visualization of the specific research question and relations between the variables tested in Study C.

Therefore, it was an aim of Study C to examine two groups using a fitness app device under randomized controlled conditions. Particularly, it was an aim of Part 1 to analyze the influence of continuous self-tracking via fitness apps on body trusting, body listening, and psychological well-being to understand the role of trust in technology as a potential moderator variable, and to identify causal relationships between body trusting and psychological well-being using multilevel analysis (Figure 63).

Figure 63. Visualization of the specific research question and relations between the variables tested in Study C.

It was a second aim of Study C to test the trust in a specific technology model in a longitudinal design to identify the stability of propensity to trust, and to examine potential causal relations within the model of trust in the specific technology of fitness apps in fitness app users. Within the integrated model of trust, *propensity to trust* is regarded as a trait-based perception of others that has been demonstrated to be stable across time and situations (e.g., Alarcon et al., 2016, 2018). In contrast, *institution-based trust* reflects context (i.e., technology) specific assumptions, and *trusting beliefs* reflect situation and information specific beliefs, potentially implying less stability over time and situations (McKnight et al., 2011). In previous research, propensity to trust has been shown to predict trusting beliefs in unfamiliar conditions (Alarcon et al., 2016). Therefore, it was an aim of Part 2 to test potential causal relations within the trust in a specific technology model (McKnight et al., 2011) in the field of fitness app usage, using structural equation modelling (SEM, Figure 64).

Figure 64. Visualization of the specific research question based on the model of Trust in echnology (McKnight et al., 2011), and the relations between the variables tested in Study C.

As the analyses of Part 1 and Part 2 include different sets of samples (i.e., Part 1 including all participants, Part 2 including fitness app users only), the sample descriptions, reliability estimations, statistical analysis, etc. vary considerably. Therefore, each part is presented separately throughout Study C. Furthermore, Part 1 and Part 2 represent distinct research questions. Thus, each part contains an individual discussion section. Overall, Part 1 of Study C contributes to the understanding of the effects and relations between fitness app usage, body trusting, and trust in technology with regards to the research framework model introduced in this work. Part 2 contributes to a more elaborate understanding of trust in technology, specifically with regards to fitness app usage.

Part 1: The Effects of Self-Tracking

It was an aim of Part 1 to examine continuous self-tracking via fitness apps by observing potential longitudinal effects. To provide a better understanding of the general (i.e., subjective feedback) vs. fitness app specific (i.e., objective feedback) processes associated with continuous self-tracking, it was an aim to implement an additional control group that monitored their physical activity via self-report, but not via fitness apps. Also, it was an aim to systematically vary the condition by implementing a specific step target in another group (i.e., 10,000 steps per day) to understand the effect of this specific app function.

In connection with the potential effects of fitness app usage on body listening, body trusting and well-being, it can be highly relevant to consider whether a fitness app user trusts the feedback provided by the fitness app. Therefore, supplementary analyses targeting the mediating role of trust in technology are provided. Furthermore, the purpose was to explore potential causal relationships between body trusting and psychological well-being. Answering these research questions, it was an aim to use a multi-method approach to gain comprehensive understanding of the inter- and intraindividual trajectories of the outcome variables. In addition to comprehensive pre- and post-questionnaires, it was an aim to conduct daily assessment (i.e., experience sampling) to provide elaborate and precise analysis of the outcomes' trajectories. This study is the first to test the effects of fitness app usage under randomized controlled conditions in a longitudinal design using experience sampling in a multilevel analysis. Furthermore, this study is the first to provide an approach testing the causality between body trusting and psychological well-being[3].

[3] The development of the research design of Part 1 was supported by Till Utesch, Paul-Christian Bürkner, Bernd Strauss, and Katharina Geukes. Paul-Christian Bürkner and Till Utesch provided support with the data analysis. Christin Resing, Laura Vieten, Alexandra Geier, and Franziska Sieber assisted with the data acquisition and data management. Christin Resing used parts of the data collected in this study for a separate analysis in her master's thesis. A preliminary draft of the results of Part 1 of Study C is available as a preprint. The modified preprint can be viewed at Psyarxiv.com https://doi.org/10.31234/osf.io/cd6t8.

Hypotheses. In a first step, the effects of self-tracking via fitness apps and the implementation of an external target of 10,000 steps per day on body listening, body trusting, and psychological well-being were examined. Therefore, it was hypothesized:

Hypothesis 1a: Self-tracking via fitness apps using objective feedback leads to higher levels of body listening, body trusting, and psychological well-being compared to self-tracking via a daily diary using subjective feedback.

Hypothesis 1b: The implementation of an external target of 10,000 steps per day leads to lower levels of body listening, body trusting, and psychological well-being compared to no such implementation.

Hypothesis 1c: Trust in technology moderates the effect of self-tracking via fitness apps on body listening, body trusting, and psychological well-being.

In a second step, the relationship between body trusting and psychological well-being was examined to provide external validity with regards to the novel construct of body trusting. As body trusting is assumed to be of adaptive nature, it was hypothesized:

Hypothesis 2a: Body trusting is associated with psychological well-being.

Hypothesis 2b: High levels of body trusting lead to higher levels of psychological well-being one day later.

Methods

Trial design. In this study, two randomized experimental groups tracked their physical activity via a wearable fitness app device and via a daily diary questionnaire. The Experimental Target (ET) group had a pre-defined step goal of 10,000 steps per day implemented in the fitness app, whereas the Experimental No Target (ENT) group did not have any step goal. The additional control group did not receive a wearable fitness app device and tracked their physical activity—like all groups—via a daily diary.

A multi-method approach was used to gain a comprehensive understanding of the inter- and intraindividual trajectories including the outcomes' variance. In addition to comprehensive pre- and post-questionnaires, a daily diary (i.e., experience sampling) method was applied. Experience sampling has been identified as a useful and elaborate technique with a large range of benefits, such as greater ecological validity, reduction in the likelihood of memory biases, and revelation on intra-individual processes (Bolger, Davis, & Rafaeli, 2003; Scollon, Prieto, & Diener, 2009). In line with studies investigating the effects of fitness app usage (Walsh, Corbett, Hogan, Duggan, & McNamara, 2016; Wang et al., 2015), an intervention time of six weeks was determined.

Prior to recruitment, the study was approved by the ethics committee of the University of Münster. The study was registered at the German Clinical Trials Register (DRKS, 2019; Grant no. DRKS00014835) and can be viewed at the WHO website http://apps.who.int/trialsearch/. Conduct and reporting of the trial was guided by the Consolidated Standards of Reporting Trials (CONSORT; Schulz, Altman, & Moher, 2010).

Participants and sample size. Participants were recruited via flyers distributed at the University of Münster, via social media, and via local newspapers around the city of Münster. The control group was separately acquired at the same time period and in the same environmental contexts, using another flyer that was blind to the intervention (i.e., fitness tracker usage). Alternatively, all three groups could have been provided with the same information that they might or might not have received a fitness tracker. It was expected that the group not being provided with a fitness tracker would have perceived inferiority to the fitness tracker groups, potentially leading to undesired group effects. Participants of the experimental groups were informed in advance that the study participation would entail the use of a wearable fitness tracker and that this would result in the disclosure of personal data due to ethical considerations. To provide clear insight into the effects between the fully randomized ET and ENT groups and the control group, two separate analyses are provided: One analysis including all three groups and an additional analysis including only the two experimental groups that is provided in the Supplements. The participants were incentivized to participate as follows. Every 20th participant completing the study won 20€. Each participating student enrolled at the University of Münster had the alternative opportunity to earn a credit of up to 5.5 hours.

The effects of fitness app usage on body listening and body trusting have yet to be examined. However, in a three month intervention, medium effect sizes of meditation practice on body listening and body trusting were found (Bornemann et al., 2015). Thus, an anticipated medium size effect of $f^2 = .18$ was estimated with regards to the expected increase in the outcome variables. A power analysis revealed that a sample size of $n = 45$ per group was required to detect a statistical effect of $f^2 = .18$, given 80% power, and $\alpha = .05$ (Soper, 2012). The dropout rate per group was estimated 10%, whereas it was expected that the dropout rate in the control group receiving no fitness tracker would be higher compared to the experimental groups receiving a fitness tracker during the intervention. It was planned to recruit 50 participants per group, which was also defined in the pre-registration. However, during the recruitment phase, 52 participants were allocated to the control group, and thus were included in the intervention and analysis. The pre-defined inclusion criteria are presented in Table 20.

Group allocation and interventions. All allocated participants were invited to fill in a computer-based questionnaire under controlled lab conditions. The questionnaires were provided via the online survey program *unipark* (Questback GmbH, 2018). Weight and height were measured in the lab to calculate the BMI. All participants signed informed consent and were asked to contact the researchers in case of technical issues or health problems. The experimental groups additionally received a fitness tracker wearable (*Fitbit Flex 2*) and instructions about the fitness tracker usage. The participants' devices and the smartphone application were set up at the lab.

Table 20

Inclusion Criteria

<u>The participants:</u>
(a) are between 18 and 40 years old, representing the main age group using fitness apps (Statista, 2017);
(b) self-report exercise behaviour of less than four hours per week on average to focus on participants who are not engaging in professional sport;
(c) have not used a fitness app for longer than two weeks within the past six months and thus represent fitness app novices;
(d) possess a smartphone with internet connection and Bluetooth function;
(e) are currently not injured or diseased, reducing the risk of being under a state which can potentially influence the capability to exercise;
(f) are not planning to travel for more than one week during the study period;
(g) are not engaging in an employment requiring night shifts on a regular basis to ensure valid daily measurement and analysis of the data.

In the ENT group, no daily step target was set. Thus, the progress bar indicating the daily covered steps did not change in the smartphone app in the ENT group (Figure 65A). In the ET group, the daily step target was set to 10,000, and the progress of reaching the step target was indicated via the progress bar on the interface (Figure 65B&C). In both ET and ENT groups, the participants could also monitor their coverage of calories, distance, and active minutes in the smartphone app. Participants in both groups were asked not to set further goals or change the app settings. During the six-weeks intervention, the participants were asked to wear the fitness tracker wristband all day long. Every evening at 9pm, all participants received identical text messages entailing a link to an online daily diary.

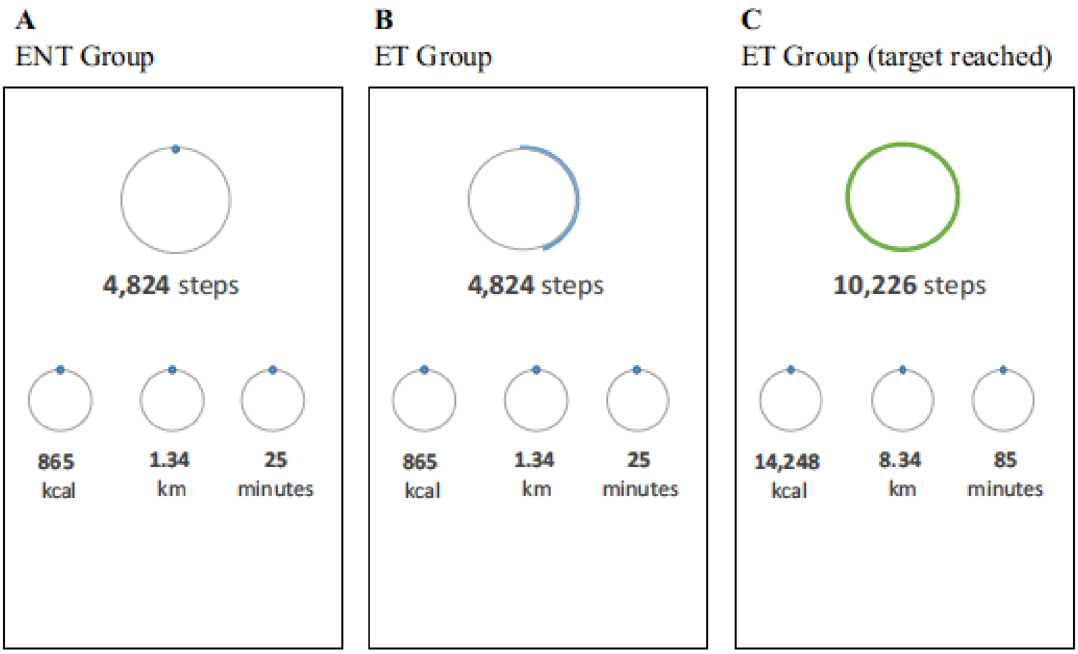


Figure 65. Visualization of the fitness app interface.

Note: A, experimental no target group; B, experimental target group; C, experimental target group (target reached).

After the six-week intervention, all participants were invited to the lab to fill in the post-test computer-based questionnaire and to return their device. The questionnaire entailed a check, assessing whether the participants had worn the fitness trackers and whether they had changed the app settings during the intervention.

Blinding. All participants were blinded to the study design and to the implementation of different groups. After the study was completed, all participants were informed about the research questions and design. The researchers were not blinded to the experimental conditions or the purpose of the study. The generation of a sequence allocation was conducted on the basis of the participants' codes. Thus, the researchers were blinded to the participants' identity during this stage. During the pre- and post-tests and the intervention, the researchers were in direct contact with the participants (e.g., providing technical assistance). Thus, they were not blinded to the participants' identity or allocation at this time. During the data analysis, all data was managed on the basis of the participants' code. Thus again, the researchers were blinded to the participants' identity, but not to the participants' group allocation.

Psychological well-being. Well-being was measured via a German version of the WHO-5 questionnaire (Brähler, Mühlan, Albani, & Schmidt, 2007). The questionnaire entails five items that are—as introduced in the original questionnaire—rated on a 6-point Likert scale (1 = *not agree at all* to 6 = *fully agree*). Good reliability and validity of the German version of the WHO-5 has been demonstrated by Brähler et al. (2007). In this study, a congeneric model fitted the data better compared to an essentially τ-equivalent model ($\Delta\chi^2[4] = 9.82$, $p = .044$), and thus, ω_H should be interpreted. Reliability in the pre-test questionnaire was $\omega_H = .77$ (Cronbach's $\alpha = .76$). In the daily diary measurement, a single item measuring well-being was used (*"I felt good today"*) and was rated on a 7-point Likert scale (1 = *not agree at all* to 7 = *fully agree*). All items created for the daily questionnaire were rated on a 7-point Likert scale with the aim to facilitate usability and comparability of the daily questionnaires.

Body trusting and body listening. To measure body trusting and body listening, the Multidimensional Assessment of Interoceptive Awareness (MAIA; Mehling et al., 2012) was used. The scale *body listening* describes active listening to body sensations to gain information about body states. The scale *trusting* refers to experiencing the body as safe and trustworthy. In the pre- and post-intervention questionnaires, body listening and body trusting were measured via the German version of the Multidimensional Assessment of Interoceptive Awareness (Bornemann et al., 2015) on a 6-point Likert scale (1 = *not agree at all* to 6 = *fully agree*). Each scale includes three items. A congeneric model fitted the data better compared to an essentially τ-equivalent model in this study ($\Delta\chi^2[2] = 6.49$, $p = .039$), and thus, ω_H should be interpreted. Reliability in the pre-test questionnaire was $\omega_H = .70$ (Cronbach's $\alpha = .68$) for body listening. For body trusting, a congeneric model fitted the data better compared to an essentially τ-equivalent model in this study ($\Delta\chi^2[2] = 13.65$, $p = .001$), and thus, ω_H should be interpreted. Reliability in the pre-test was $\omega_H = .75$ (Cronbach's $\alpha = .74$). In the daily diary questionnaire, single items were used to measure body listening ("*I listened to my body today*") and body trusting ("*I trusted my body today*") and were rated on a 7-point Likert scale (1 = *not agree at all* to 7 = *fully agree*).

Statistical methods. To rule out potential reactivity effects, the analyses of the daily data were conducted excluding the first three intervention days. Furthermore, the incomplete day of measurement at the post-test was excluded, as it was defined in the pre-registration of this study. Thus, considering a 42 days intervention, daily diary data of 38 days was analyzed. All participants were considered in an intention-to-treat (ITT) analysis. The data sets were screened for outliers and implausible data. Bayesian linear regressions were conducted to tests potential group differences in baseline characteristics.

Main Analysis. To examine the main outcome variables across time and groups, ordinal Bayesian multilevel modelling was conducted, with longitudinal body listening, body trusting, and well-being as ordinal dependent variables. The ordinal models assume the single item Likert-scores to be originating from the categorization of a latent continuous and normally distributed variable (Bürkner & Vuorre, 2018). This procedure not only facilitates interpretation, but also ensures valid inference based on Likert-scores, as classical analyses of such scores may have serious problems (Liddell & Kruschke, 2018). To account for potential heterogeneity, the latent variables' variances were modelled as varying across time and groups, with the variance of the control group at the initial time point being fixed at one for reasons of identification (Bürkner & Vuorre, in press). In the models, intervention days were entered on level 1, and person characteristics including the group condition were entered on level 2. The time variable *intervention days* was scaled to only take on values between 0 (first day) and 1 (last day) to ease interpretation of regression coefficients. The grouping variable was dummy coded with the control group as reference category.

Similarly, pre-post data of body listening, body trusting, and well-being questionnaires were analyzed via ordinal Bayesian multilevel modelling using single item Likert-scores, while controlling for the dependency of observations belonging to the same item (Bürkner, 2017) as scales at pre- and post-treatment consisted of more than one item. Again, time of measurement was entered on level 1, and person characteristics including group condition were entered on level 2. Both time and grouping variable were dummy coded with pre-test and control group being the reference categories, respectively. Latent variances were allowed to vary across time and groups in the same way as in the analysis of daily data. All analyses described above were conducted entering (a) all groups; (b) only the randomized ET and ENT groups.

Moderator analyses. In a further examination, all analyses described above were conducted, each entering the moderator variables *trusting stance in technology*, *pre-measured physical activity*, and *BMI* to identify potential moderator effects. To test the moderating effect of trust in technology across fitness app novices, a scale was needed that could validly measure trust in technology in unexperienced users. Based on the results found in Study A, the scale *trusting stance* (McKnight et al., 2011) measuring propensity to trust in technology was used in this study to measure trust in the fitness app. For a full description and coefficients of this variable, see the methods section of Part 2.

Body trusting and well-being. Additionally, exploring potential causal effects between body trusting and well-being, each variable was entered and regressed on the predictor variable measured one day earlier, thus controlling for auto-correlation.

The overall results could have potentially been biased due to some participants' properties varying systematically across groups as the control group was not randomized.

Therefore, it was controlled for the participants' age, gender, and educational status in all analyses in the hope to at least partially account for non-randomization. Data analyses were conducted via the programming language *R* (R Core Team, 2016) with the interface RStudio (RStudio Team, 2015). For the Bayesian multilevel analysis, the R package *brms* (Bürkner, 2017) based on Stan (Carpenter et al., 2017) was used. The fully reproducible analysis including open data, open code, open results (i.e., including the coefficients of all preliminary, main, supplementary, and moderator analyses), and all supplementary tables of this study are provided on OSF https://osf.io/uz3e9/?view_only=a6b2691c5c08474ca0ff0d7f0626d2f5.

Results

Participant flow and baseline data. The recruitment period started on 3rd January 2018 and ended after the pre-defined intervention time on 5th June 2018. The participant flow is presented in a flow-chart guided by the CONSORT (Schulz et al., 2010) criteria (

Figure 66).

In the ET and ENT groups, each n = 50 participants received the allocated intervention. In the control group, n = 52 persons participated. A total of n = 7 participants did not fill in the post-test questionnaire. Thus, the data of these participants could not be used for the pre-post-analyses. In the ET group, one participant discontinued the intervention after 26 days due to health issues. In the control group, two participants discontinued the intervention at the day of the pre-test and after five days without reasons given. All participants who discontinued the intervention were included in the ITT analysis. Thus, the data of all n = 152 participants were included in the multilevel daily diary analysis.

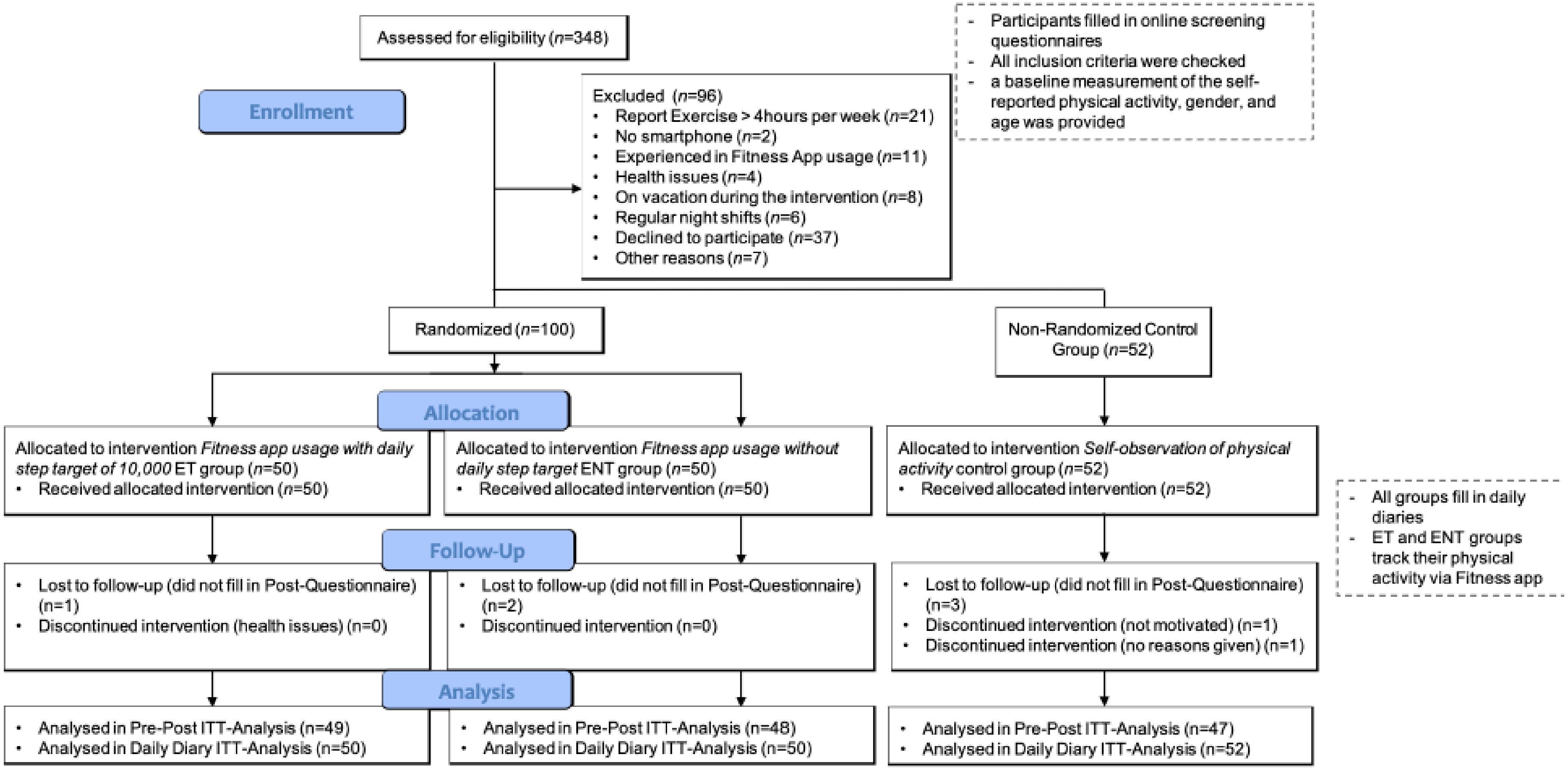


Figure 66. Flow Diagram guided by CONSORT.

Note: The control group was not randomized or parallelized in order to ensure blinding to the study design. ET, experimental target group; ENT, experimental no target group; ITT, intention to treat.

Table 21

Baseline Characteristics Measured in the Pre-Test

	Range	**Group 1 (n = 50)**		**Group 2 (n = 50)**		**Group 3 (n = 52)**	
		M	***SD***	***M***	***SD***	***M***	***SD***
Age (years)	18–40	25.56	4.54	25.78	4.78	22.73	4.32
Body mass index (BMI)	17–32	22.33	3.11	22.14	2.86	21.74	3.18
Physical Activity (hours per week)	0–4	2.21	1.28	2.23	1.09	2.58	1.15
Trusting Stance in Technology	1–7	4.79	1.07	4.87	1.34	4.31	1.41
Body Listening	1–6	3.69	0.84	3.62	0.93	3.82	0.90
Body Trusting	1–6	4.59	0.80	4.58	0.84	4.71	0.88
Well-Being	1–6	3.73	0.83	3.66	0.78	3.66	0.79

Note. M = mean; *SD* = standard deviation.

The baseline characteristics of the $N = 152$ participants measured in the pre-test are presented in Table 21. In the ET group, $n = 36$ participants (72%) were female, and $n = 32$ participants (64%) were students. In the ENT group, $n = 40$ participants (80%) were female, and $n = 33$ participants (66%) were students. In the additional control group, $n = 42$ participants (81%) were female and $n = 49$ participants (94%) were students. With regards to the randomized experimental groups, no differences in age, gender, trusting stance, physical activity, BMI, body trusting, body listening, and psychological well-being were observed. In comparison of the additional control group with the other groups, no differences in physical activity, BMI, body trusting, body listening, and psychological well-being were observed. However, the control group was younger than the ET (95%-CI = [1.08, 4.59]) and ENT groups (95%-CI = [1.31, 4.83]). Furthermore, the control group reported lower levels of trusting stance than the ENT group (95%-CI = [0.03, 1.05]). A correlation matrix of all variables assessed in this study is provided in the Supplements (Supplement A, Table 1). Furthermore, the means of the outcome variables assessed in the post-test are provided in the Supplements (Supplement A, Table 2).

Daily data. With regards to the analysis of body trusting and well-being across persons, neither time effects nor time-group interaction effects were found. In the comparison of all groups, the ENT group reported lower body trusting compared to the control group at the beginning (see Table 22, for a visualization see Figure 67). However, no time or time-group interaction effects were observed. An additional analysis facing the comparison of only the randomized ET and ENT groups was conducted. The detailed results are provided in the Supplements (Supplement A, Tables 3 and 4). With regards to the main analysis, again, no significant effects were observed. Here, the ET group reported higher levels of body trusting and body listening compared to the ENT group at the beginning.

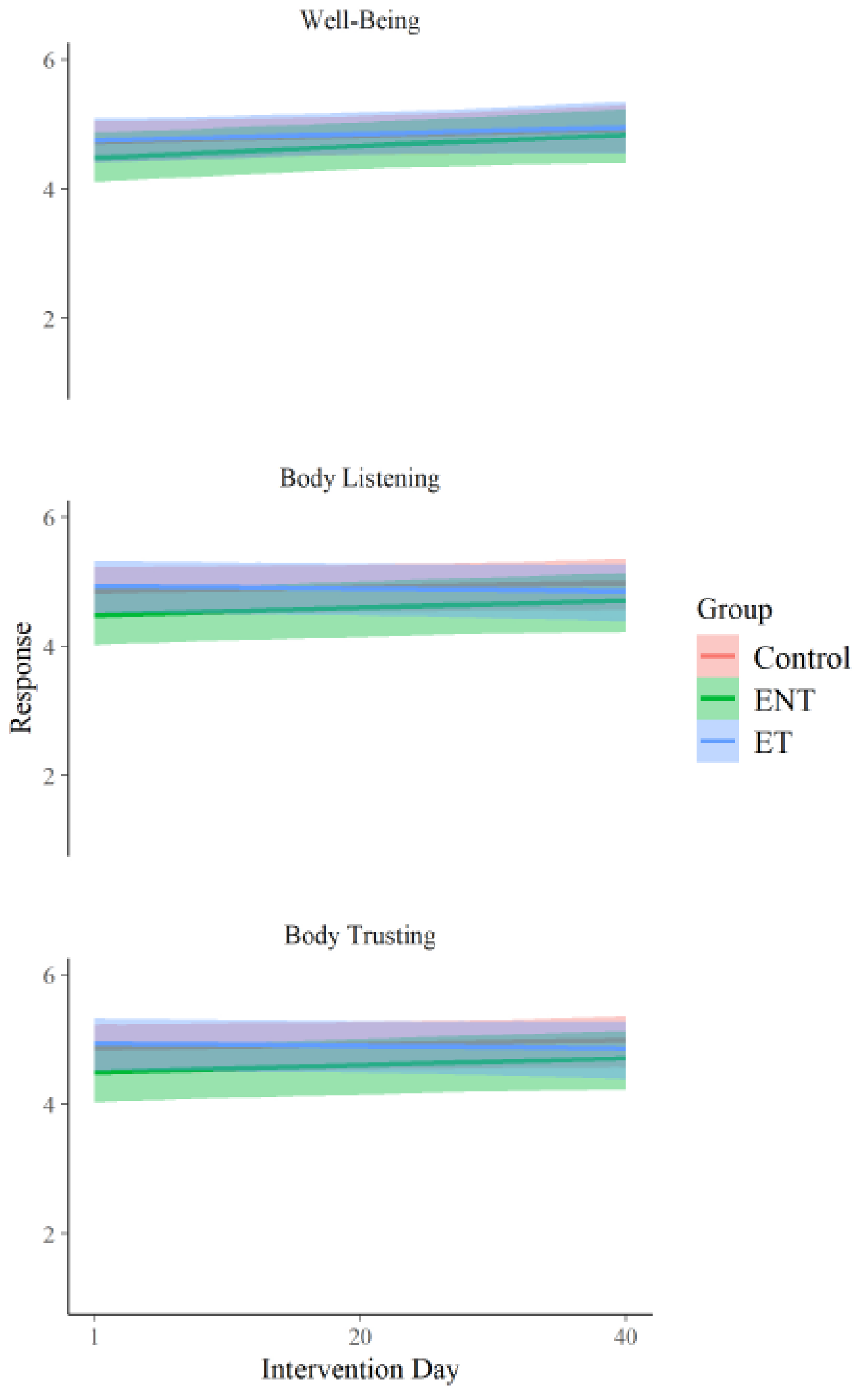


Figure 67. Visualization of the daily analysis of psychological well-being, body listening, and body trusting.

Note: Control, control group; ENT, experimental no target group; ET, experimental target group.

Table 22

Results of the Multilevel Analyses of Well-Being, Body Listening, and Body Trusting across Persons

	Daily measurement				Pre-post measurement			
	b	**95%-CI**	***SD*$_{subjects}$**	**95%-CI**	***b***	**95%-CI**	***SD*$_{subjects}$**	**95%-CI**
Well-being								
Intercept[a]	-	-	0.57	[0.47, 0.68]	-	-	0.88	[0.72, 1.06]
Time	0.13	[–0.14, 0.41]	0.73	[0.58, 0.90]	**0.49**	**[0.14, 0.87]**	1.12	[0.90, 1.37]
ET Group	0.03	[–0.23, 0.31]			0.02	[–0.37, 0.40]		
ENT Group	–0.18	[–0.45, 0.09]			–0.05	[–0.46, 0.37]		
Time:ET	–0.01	[–0.40, 0.37]			–0.31	[–0.84, 0.19]		
Time:ENT	0.11	[–0.28, 0.51]			–0.46	[–1.01, 0.05]		
Body Listening								
Intercept[a]	-	-	0.66	[0.55, 0.77]	-	-	0.97	[0.77, 1.20]
Time	0.13	[–0.14, 0.37]	0.63	[0.48, 0.79]	0.12	[–0.12, 0.37]	0.15	[0.01, 0.40]
ET Group	0.07	[–0.23, 0.37]			–0.15	[–0.64, 0.34]		
ENT Group	**–0.35**	**[–0.66, –0.03]**			–0.29	[–0.78, 0.18]		
Time:ET	–0.17	[–0.54, 0.19]			0.19	[–0.18, 0.56]		
Time:ENT	–0.02	[–0.38, 0.32]			–0.02	[–0.37, 0.34]		
Body Trusting								
Intercept[a]	-	-	0.67	[0.56, 0.78]	-	-	1.23	[0.96, 1.54]

Time	0.08	[–0.16, 0.32]	0.62	[0.48, 0.78]	0.08	[–0.24, 0.41]	0.47	[0.04, 0.85]
ET Group	0.07	[–0.23, 0.39]			–0.13	[–0.75, 0.46]		
ENT Group	–0.28	[–0.59, 0.03]			–0.13	[–0.70, 0.41]		
Time:ET	–0.18	[–0.52, 0.15]			0.26	[–0.21, 0.74]		
Time:ENT	0.05	[–0.31, 0.39]			–0.19	[–0.67, 0.24]		

Note. b = mean regression coefficient across persons; $SD_{subjects}$ = standard deviation of the regression coefficient across persons; 95%-CI = 95%-credibility interval; regression coefficients whose credibility intervals do not include 0 are highlighted in bold.

[a] Since ordinal models have multiple intercepts, these are not reported here for brevity.

Table 23

Latent Outcome Variability Compared Across Groups and Time

	Daily measurement				Pre-post measurement			
	First Day		Last Day		Pre-Test		Post-Test	
	σ	**95%-CI**	**σ**	**95%-CI**	**σ**	**95%-CI**	**σ**	**95%-CI**
Well-being								
Control Group[a]	1	-	**0.86**	**[0.74, 0.98]**	1	-	1.05	[0.88, 1.25]
ET Group	1.05	[0.94, 1.18]	**0.86**	**[0.76, 0.96]**	0.99	[0.82, 1.16]	0.97	[0.82, 1.15]
ENT Group	0.99	[0.89, 1.11]	**0.84**	**[0.75, 0.95]**	1.05	[0.88, 1.23]	0.99	[0.82, 1.18]
Body Listening								
Control Group[a]	1	-	0.92	[0.79, 1.06]			0.97	[0.77, 1.21]
ET Group	1.12	[0.99, 1.26]	**0.85**	**[0.76, 0.95]**	0.87	[0.70, 1.08]	1.04	[0.83, 1.28]
ENT Group	1.10	[0.98, 1.23]	**0.88**	**[0.78, 0.99]**	1.12	[0.91, 1.36]	1.08	[0.87, 1.33]
Body Trusting								
Control Group[a]	1	-	0.89	[0.76, 1.03]	1	-	1.03	[0.79, 1.33]
ET Group	1.02	[0.91, 1.14]	**0.81**	**[0.72, 0.91]**	**1.28**	**[1.01, 1.59]**	**1.31**	**[1.03, 1.65]**
ENT Group	1.03	[0.91, 1.15]	**0.75**	**[0.67, 0.85]**	1.10	[0.86, 1.37]	0.96	[0.76, 1.22]

Note. σ: latent standard deviation obtained from ordinal models varying across time and groups; 95%-CI: 95%-credibility interval of σ; standard deviations whose credibility intervals do not include 1 are highlighted in bold.

[a] The residual standard deviation of the control group measured in the pre-test is fixed to 1 for reasons of identifiability.

Pre-post data. Targeting the pre-post data, neither time or group effects nor group-time interaction effects on body listening and body trusting were found (Table 22). For well-being, significant time effects were found. However, no group or group-time interaction effects were observed. Body listening measured in the pre-test was negatively related to pre-measured trusting stance in technology ($b = -0.39$, 95%-CI = [–0.68, –0.10]), and BMI ($b = -0.10$, 95%-CI = [–0.18, –0.02]). However, no time-group interaction effects were found. In the additional analysis facing the comparison of only ET and ENT groups (see Supplement A, Tables 3 & 4), neither group nor time or time-group interaction effects were found.

Variance of the outcomes. Overall, the variation across persons in starting values (intercepts) and in changes over time (slopes) were high in all analyses (Table 23). Small negative correlations between intercepts and slopes were found in the analysis of well-being ($r = -.40$, 95%-CI = [–.58, –.19]), body listening ($r = -.36$, 95%-CI = [–.56, –.11]), and body trusting ($r = -.28$, 95%-CI = [–.49, –.05]). In total, the variation of the outcomes decreased over time, although by a rather small amount, while no differences across groups were found.

Moderator analyses. In all analyses, moderator variables were entered for both pre-post and daily analyses on body listening, body trusting, and well-being. For all tested moderator variables (i.e., trusting stance in technology, pre-measured physical activity, and BMI), no substantial effects were observed (see online OSF supplement results for details). Controlling for age, gender, and education level, mostly no influence on the outcome variables were observed. However, body listening was higher in females in the daily assessment ($b = 0.30$, 95%-CI = [0.02, 0.60]), but not in the pre-post assessment. Well-being was higher in non-students in the pre-post assessment ($b = 0.55$, 95%-CI = [0.17, 0.92]), but not in the daily assessment.

Body trusting and well-being. Further analyses targeted potential causal effects via a cross-lagged analysis. When not controlling for auto-correlation, body trusting was positively related to well-being one day later ($b = 0.06$, 95%-CI = [0.03, 0.10]). Vice versa, well-being was also positively related to body trusting one day after ($b = 0.07$, 95%-CI = [0.03, 0.10]). However, after controlling for lag-one auto-correlation, well-being was unrelated to body trusting one day after ($b = 0.00$, 95%-CI = [–0.04, 0.05]), and body trusting was negatively related to well-being one day after ($b = –0.07$, 95%-CI = [–0.12, –0.02]). The lag-one auto-correlation coefficient for body trusting was $b = 0.12$ (95%-CI = [0.07, 0.17]), and $b = 0.23$ (95%-CI = [0.18, 0.28]) for well-being, thus demonstrating a somewhat stronger auto-correlation for well-being.

Discussion

People engaged in self-tracking hope to find patterns in their behavior, find causes and trajectories of healthy or unhealthy behavior (Moschel, 2013). Digital media provide a quantification of subjective states that imply objectiveness and appear to be true and trustworthy, helping users to understand and potentially modify their behavior (Crawford et al., 2015). In this context, self-tracking via fitness apps has been described as a means to practice body awareness and body trusting (Sharon & Zandbergen, 2017; van Dijk, Westerink, Beute, & IJsselsteijn, 2015). Hence, it was an aim of this study to understand the process of continuous self-tracking via fitness apps on body trusting, body listening, and psychological well-being by observing potential longitudinal effects via the comprehensive analysis of pre-post and daily data. To provide a better understanding of the general (i.e., subjective feedback) vs. fitness app specific (i.e., objective feedback) processes associated with continuous self-tracking, one group was implemented that monitored their physical activity via self-report, but not via a fitness app. The condition was systematically varied by implementing a specific step target in one group (i.e., 10,000 steps per day) to understand the effects of this specific app function.

Body trusting and body listening. It was a main aim of this study to investigate how self-tracking of physical activity via fitness apps can influence aspects of self-reported body awareness, hypothesizing that self-tracking via fitness apps (and thus, using objective feedback) can lead to higher levels of body trusting, body listening, and psychological well-being compared to no such feedback. Furthermore, it was hypothesized that the implementation of an external step target undermines body trusting, body listening, and psychological well-being. It has been outlined that abilities in body listening and body knowledge can be beneficial for improving health conditions and pain management (Chen, Carriere, & Kaplan, 2017; Mehling et al., 2009). Therefore, body listening and body trusting have been associated with higher levels of subjective well-being (Brani et al., 2014). Furthermore, it has been discussed that fitness app usage can be regarded as a way to practice mindfulness and body awareness (Sharon & Zandbergen, 2017). However, the results of all daily and pre-post analyses regarding body listening and body trusting indicated no change during the six-weeks intervention. No group effects and no group-time interaction effects were observed. The results indicate that neither self-observation of physical activity induced via a daily diary measurement nor the objective feedback provided by the app lead to higher levels of self-reported body listening or body trusting across the participants. Therefore, *Hypotheses 1a* and *1b* were not confirmed.

Tracking physiological parameters has also been associated with a higher correspondence of perceived stress and heart rate (van Dijk et al., 2015). Physiological feedback such as heart rate can be observed and also regulated in direct and instant feedback. However, tracking of one's own burnt calories or covered steps represent an ex-post indicator of physical activity and might not be helpful in calibration or better understanding of physiological processes. Thus, it might be unlikely that external feedback provided by the fitness app can influence body listening and body trusting.

Well-being. The World Health Organization (WHO) has defined mental health and psychological well-being as important factors of general health in their core principles (WHO, 1995). Whereas the positive effects of fitness app usage on physical activity have been stressed in a range of studies (Moschel, 2013; Schoeppe et al., 2016), the effects on quality of life have been analyzed in few studies to date. The results of this study indicate that neither self-monitoring of physical activity via fitness apps nor the implementation of an external step target substantially affects psychological well-being during six weeks' fitness app usage.

Aligned with the effects on well-being found in this study, an RCT investigating the effects of an eight week online physical activity intervention including self-monitoring found improvement in walking time, whereas improvements in overall well-being and mental health were not found respectively (Maher et al., 2015). In a similar RCT study, the effects of fitness app usage in primary care patients using fitness apps were examined (Glynn et al., 2014). After the eight weeks intervention, improvement in step count was found whilst well-being had not increased. In contrast, fitness app users in a sample of recreational runners reported higher levels of running activity, stated to feel better about themselves, and felt more like an athlete (Dallinga, Mennes, Alpay, Bijwaard, & de la Faille-Deutekom, 2015). These results indicate that the effects of fitness app usage on psychological well-being can be task specific. In active and sportive persons, the specific activity can be of high valence and might be connected to well-being. However, in non-sportive persons, physical activity might be of lower relevance. Although fitness app usage has been found to beneficial, for example to enhance health behavior or to find patterns of unhealthy behavior (e.g., Moschel, 2013; Schoeppe et al., 2016), also psychological risks such as the perception of pressure, fear, and even symptoms of eating disorders have been discussed in the context of fitness app usage

(Lupton, 2013; 2014; Simpson & Mazzeo, 2017). Therefore, it can be assumed that neither overall outstanding psychological benefits nor risks emerge in the context of fitness app usage. However, it should be noted that a high variability was observed, implying the necessity to elaborate on the differentiated risks and benefits across specific user groups in future studies.

Moderator analyses. It was hypothesized that the effect of self-tracking via fitness apps on body trusting, body listening, and psychological well-being is moderated by trust in technology. In ancillary analyses targeting the moderating effects of trust in technology, physical activity, or BMI, no effects were found over time. The results indicate that the trajectories of body listening, body trusting, and well-being over time are neither influenced by the trust of a person in the feedback provided by the app nor by their body constitution or physical activity. Therefore, *Hypothesis 1c* was not confirmed. However, body listening measured in the pre-test was negatively related to pre-measured BMI. These results indicate that a high BMI can be associated with lower body trusting, as a high BMI might also potentially lead to health risks and dissatisfaction with the body (Paxton, Neumark-Sztainer, Hannan & Eisenberg, 2006; WHO, 2017). Also, body listening measured in the pre-test was negatively related to pre-measured trust in technology. Digital media can provide a tool to produce “hard facts” and a more “objective” reality (En & Pöll, 2016, p. 44). Hence, self-tracking is described as a means to practice *control*, consequently leading to risk reduction. Therefore, persons with little capabilities in body listening might lay higher trust in objective feedback provided by fitness apps. Controls (such as fitness apps) influence the evaluation of risk (Schoorman et al., 2007) and can bridge the difference between perceived risk and trust (i.e., low body trusting) by lowering the perceived risk. Although the aspect of risk is implied in this context, the effect was only found for body listening, but not for body trusting. These results imply that body trusting might be considered as a concept that is mainly unrelated with trust theory.

Variance of the outcomes. The variations across persons in starting values (intercepts) and in changes over time (slopes) were high in all analyses. The results indicate that the outcomes of fitness app usage are highly user specific and might depend on a set of inter-individual and contextual factors, as already indicated above. To gain a deeper understanding of the trajectories of body listening, body trusting, and well-being, the residual variability of the outcomes across time and groups was analyzed as well. In the daily analyses, the residual variation decreased slightly over time but did not vary across groups. Thus, the predictability of the participants' responses increased from the beginning towards the end of the study, which may be a result of participants answering more consistently due to their increased experience with the study procedures (i.e., questionnaires). Such a decrease in residual variation over time was not found in the pre-post analyses. Instead, the residual standard deviation in body trusting differed slightly across groups without a notable change from pre- to post-measurement.

Body trusting and well-being. Elaborating on causal relations between body trusting and psychological well-being, it was hypothesized that body trusting is related to psychological well-being and that high levels of body trusting lead to higher levels of psychological well-being one day later. In alignment with the results of a range of other studies (Brani et al., 2014; Köteles et al., 2016), body trusting was found to be associated with future well-being in this study. When not controlling for auto-correlation in daily well-being and body trusting, well-being was positively associated with body trusting one day after and, vice versa, body trusting was positively associated with well-being one day after. However, when controlling for auto-correlation via cross-lagged analyses to explore potential causal effects of body trusting on well-being (and vice versa), well-being was unrelated to body trusting one day after, while body trusting was slightly negatively related to well-being one day after. Therefore, *Hypothesis 2a* was confirmed and *Hypothesis 2b* could not clearly be confirmed. One explanation for the latter finding is that besides aspects of well-being, body trusting might also include aspects of less positive valence that might be negatively associated with well-being, and thus lead to a negative effect when controlling for well-being in body trusting. In sum, a clear connection between body trusting and well-being was found, however, the exact nature of this connection still remains uncertain and needs to be explored in further studies with even more complex designs.

Strengths and limitations. In this study, the effects of fitness app usage and the implementation of a specific external step target were examined in a multi-method approach. In addition to comprehensive pre- and post-questionnaires, the outcome variables were assessed via an experience sampling method, using state-oriented items (e.g., "*I listened to my body today*"). Thus, a comprehensive analysis of the trajectories and variability of the outcome variables was possible. Overall, high variability across time and persons was observed and could not be explained by the broad range of moderators that were assessed. The results of this study provide a first insight into the psychological effects of fitness app usage, however indicating that more specific and elaborate studies are needed to fully understand the trajectories and potential influencing factors on the variability in well-being and aspects of body awareness. To shed light onto these processes, it could be interesting to identify more potential influences moderating the effects of fitness app usage (e.g., personal preferences and goals, familiarity with apps, etc.) via exploratory quantitative but also via qualitative methods.

In this study, an intention-to-treat analysis (ITT) was applied, including all participants in the analysis who were allocated to a group, inconsiderate of dropout or non-adherence. ITT analyses are a widely used method in clinical research and provide a range of advantages (Bondemark & Abdulraheem, 2017; DeMets & Cook, 2019). For example, ITT analyses can approach treatment circumstances under natural conditions as all participants—including those who dropped out—are considered. Also, the risk of selection effects (such as self-selection bias) or overestimation of effects including Type I errors are reduced. However, ITT analyses also neglect whether participants have de facto experienced the treatment or not. Therefore, it has been outlined that the true effect size is likely to be underestimated in ITT analyses (Currow, Plummer, Kutner, Samsa, & Abernethy, 2012; Rossi, 2014).

The two experimental ENT and ET groups were fully randomized, and the procedure met all criteria for RCTs set forth in the CONSORT statement. The control group was separately acquired—however at the same time period and in the same contexts—using another flyer that was blind to the intervention (i.e., fitness tracker usage). Alternatively, all three groups could have been randomized, and thus could have been provided with the same information that they might or might not receive a fitness tracker. However, it was expected that the group not being provided with a fitness tracker could have perceived inferiority to the fitness tracker groups, potentially leading to undesired and uncontrollable group effects. Therefore, it was an advantage of the study that all participants were blinded to the study design. Considering hypothetical biases across groups, it was attempted to control for potentially relevant variables (i.e., age, gender, educational status). However, potential specific group effects influencing the results cannot be fully excluded. For example, people recruited in different groups might have been qualitatively different from those recruited for a study that uses fitness apps. Furthermore, few pre-measured differences (i.e., in body listening) were observed. Overall, future studies following a similar study design could investigate the effects and sample distributions in a completely randomized design, informing all participants that the study might or might not include fitness app wearable usage.

Implications and conclusion. This study was designed to gain a broader understanding of the psychological benefits and risks of fitness app usage and the implementation of a specific external step target on psychological well-being and aspects of self-reported body trusting, body listening, and psychological well-being. Beyond the background of both multiple risks and benefits associated with fitness app usage, it was an aim to assess whether fitness app usage can be beneficial for psychological health related aspects such as well-being and body trusting. Therefore, the results of this study can contribute to the evaluation whether fitness app usage should be advised or not. The results of this study contribute to a small but growing body of research indicating that fitness app usage does neither positively nor negatively influence psychological well-being. Moreover, this study is the first to investigate potential effects on body listening and body trusting. Further studies are needed to underpin these results, especially with regards to aspects of body awareness and other non-physical health outcomes. Considering the large variability of effects, potential positive effects can be assumed under specific conditions that are to be identified in further studies. Supporting these beneficial effects of fitness app usage on physical activity, app developers might lay a pronounced focus on promoting a great range of specific app functions. These settings could be designed to satisfy diverse and individual user specific needs and preferences. For instance, a recreational runner might benefit from app functions complementing his or her exercise related preferences. In contrast, a physically inactive person would benefit from other settings that better match his or her needs. The identification of such individual specific needs should be identified in future studies. Recently, self-tracking via fitness apps has also been discussed to render norms and expectations about healthy behavior (Lupton, 2013). These could convey fear and might even lead to obsessive self-surveillance and hazard a person's well-being. Therefore, people were advised not to use fitness apps (Lupton, 2013; 2014). However, these assumptions are yet lacking empirical foundation. The results found in this study rather imply that fitness app usage does not hazard psychological well-being, however it does not foster psychological well-being either. Overall, the results indicate that fitness app usage and the application of an external step target cannot support the overall improvement of psychological well-being, body listening, or body trusting. However, a large variability in effects was observed, providing a first basis of evidence that the effects of fitness app usage are highly individual.

Part 2: Longitudinal Examination of Trust in Technology

It was a second aim of Study C to test potential causal relations and the temporal stability of the trust in a specific technology model (McKnight et al., 2011) in the field of fitness apps. This study is the first to test this model in a longitudinal design. As found in Study A, *propensity to trust* can be measured in both stages of usage and non-usage, leading to the context and technology specific *institution-based trust* and to the situation specific *trusting beliefs* that can be measured during post-adaption usage of a technology (McKnight et al., 2011). Therefore, *propensity to trust* measured in fitness app novices during the pre-test of Study C was used to predict *propensity to trust*, *institution-based trust*, and *trusting beliefs* measured after six weeks' fitness app usage. Thus, based on the data obtained in Study C, it was possible to test (1) the stability of propensity to trust in fitness app novices after six weeks' fitness app usage; and (2) whether propensity to trust in fitness app novices influences the degree of institution-based trust measured after six weeks' fitness app usage. As the sample included the participants of two experimental groups with varying conditions (i.e., a step target of 10,000), it was an aim to provide a measurement of invariance across these groups in an additional analysis to evaluate potential group effects.

Hypotheses. The longitudinal stability of trusting stance and potential causal relations within the model of trust in technology on the field of fitness apps were tested. Therefore, it was hypothesized:

Hypothesis 3a: Propensity to trust is stable over six weeks' time.

Hypothesis 3b: High levels of propensity to trust lead to higher levels of institution-based trust measured six weeks later.

Methods

The sample used in Part 2 was a subsample assessed in Study C, entailing the group of fitness app users (explicitly, ET and ENT groups, each entailing $n = 50$). The total of $n = 100$ participants were fitness app novices who were unexperienced to the usage of fitness apps. Therefore, only propensity to trust was measured during the pre-test (T1), whereas all three aspects of trust in a technology were measured during the post-test (T2) six weeks later.

Trust in technology. The German version of questionnaire for trust in a specific technology (McKnight et al., 2011), adapted to the context of fitness apps was used. The total questionnaire includes 15 items that were rated on a 7-point Likert scale. Scales measuring the propensity to trust were *trusting stance in general technology* (3 items), and *faith in general technology* (4 items). For institution-based trust, the scales *structural assurance* (4 items) and *situational normality* (4 items) were applied. To measure trusting beliefs, the scales *reliability* (4 items), *functionality* (3 items), and *helpfulness* (4 items) were used. The original and the translated questionnaires are provided in a supplementary file on https://osf.io/t4gfe/?view_only=61af3bab53bf4ea3837b8c4a246afbf4. To estimate reliability, scales were analyzed using Mc Donald's ω_H, because a congeneric model fitted the data better than an essentially τ-equivalent model ($\Delta\chi^2[14] = 85.57$, $p < .001$). Reliability coefficients ranged from $.65 \leq \omega_H \leq .91$ (see Table 24 for details).

Statistical analysis. First, the data was inspected via Mardia tests for normality, skewness, and kurtosis. The coefficients indicated an absence of multivariate normality ($\chi^2 = 2523.43$ for skewness ($p < .001$), and $z = 3.88$ for kurtosis ($p < .001$). Thus, the scaled estimator MLM was used. A Q-Q-Plot presenting the theoretical and sample distribution of standard errors is provided in Figure 68. Multivariate normality of standard errors is indicated when the standard errors are located close to the diagonal.

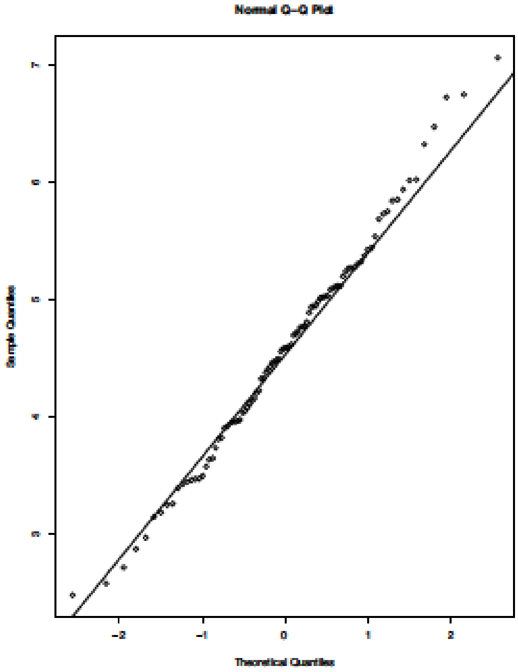


Figure 68. Q-Q-Plot indicating the theoretical and sample distributions of standard errors.

In the analysis of the hypothesized models, CFAs and SEMs were conducted. In a first step, individual CFAs for each component of propensity to trust T1, propensity to trust T2, institution-based trust T2, and trusting beliefs T2 were conducted. In a second step, a SEM was entered entailing propensity to trust T1 leading to propensity to trust T2 and institution-based trust T2 (Figure 69). As the assumptions of multivariate normality were not met, the scaled estimator *MLR* with robust standard errors and a scaled test statistic was used in the SEM. Missing values were handled using the full information maximum likelihood *fiml*. An acceptable model fit was evaluated on the basis of cut-off criteria (CFI close to > .95, TLI close to > .95, RMSEA close to < .06, SRMR close to < .08) proposed by Hu and Bentler (1999). Statistical analyses were conducted via the *System for Statistical Computation and Graphics R* (R Core Team, 2016) using the packages *lavaan* (Rosseel, 2012) and *semTools* (semTools Contributors, 2016). The online link to the he original data and open material such as the codebook including all items have been provided in the methods section of Part 1.

Table 24

Item Characteristics of All Scales Measuring Trust in Technology Assessed in this Study

	M	*SD*	*SE*	Skewness	Kurtosis	α	ω_H
T1 (n = 100)							
Trusting Stance	4.83	1.21	0.12	–0.73	0.49	.85	.87
Faith in General Technology	4.72	0.70	0.07	–0.50	1.36	.65	.65
T2 (n = 97)							
Trusting Stance	4.65	1.49	0.15	–0.71	–0.34	.91	.91
Faith in General Technology	4.53	0.91	0.09	–0.45	–0.20	.72	.73
Structural Assurance	3.82	1.13	0.11	–0.60	–0.21	.82	.83
Situational Normality	3.44	1.30	0.13	–0.09	–0.91	.86	.86
Reliability	3.81	1.39	0.14	–0.05	–0.59	.90	.91
Functionality	3.77	1.44	0.15	–0.19	–0.99	.86	.86
Helpfulness	3.47	1.14	0.12	–0.47	–0.51	.81	.82

Note. All items were measured on a 7-point Likert scale. In order to facilitate interpretation of reliability coefficients, α is reported in addition to ω_H.

Table 25

Bivariate Correlations of All Scales Measuring Trust in Technology Assessed in this Study (n = 97)

	1.	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**	**9.**
1. Faith in General Technology T1	-	.51**	.38**	.25	.30	.14	.12	.16	.14
2. Trusting Stance T1		-	.32**	.64**	.31*	.21	.23	.27	.11
3. Faith in General Technology T2			-	.54**	.44**	.52**	.57**	.57**	.51**
4. Trusting Stance T2				-	.44**	.36**	.32*	.30*	.20
5. Structural Assurance T2					-	.48**	.38**	.28	.39**
6. Situational Normality T2						-	.68**	.67**	.74**
7. Reliability T2							-	.59**	.61**
8. Functionality T2								-	.71**
9. Helpfulness T2									-

Note. All items were measured on a 7-point Likert scale; in order to facilitate interpretation of reliability coefficients, α is reported in addition to ω_H; * $p < .05$; ** $p < .01$.

Results

The item characteristics of the scales are presented in Table 24 and the bivariate correlations are presented in Table 25. Overall, scales measuring propensity to trust indicated higher mean values than the scales measuring institution-based trust and trusting beliefs. The CFA analyses of each aspect of trust showed good model fits for propensity to trust T1, propensity to trust T2, institution-based trust T2, and trusting beliefs T2 (Table 26).

In the main analysis, the longitudinal sequence of the model was tested using a SEM (see Figure 69 and Table 26). Overall, a non-sufficient model fit was indicated ($N = 100$, $\chi^2 = 346.79$, $df = 197$; $p < .001$; CFI = .86, TLI = .84; RMSEA = .089 [.073,.104]; SRMR = .089). However, all factor loadings were highly significant (all $p < .001$), ranging from $.51 \leq \lambda \leq .98$ (Figure 69).

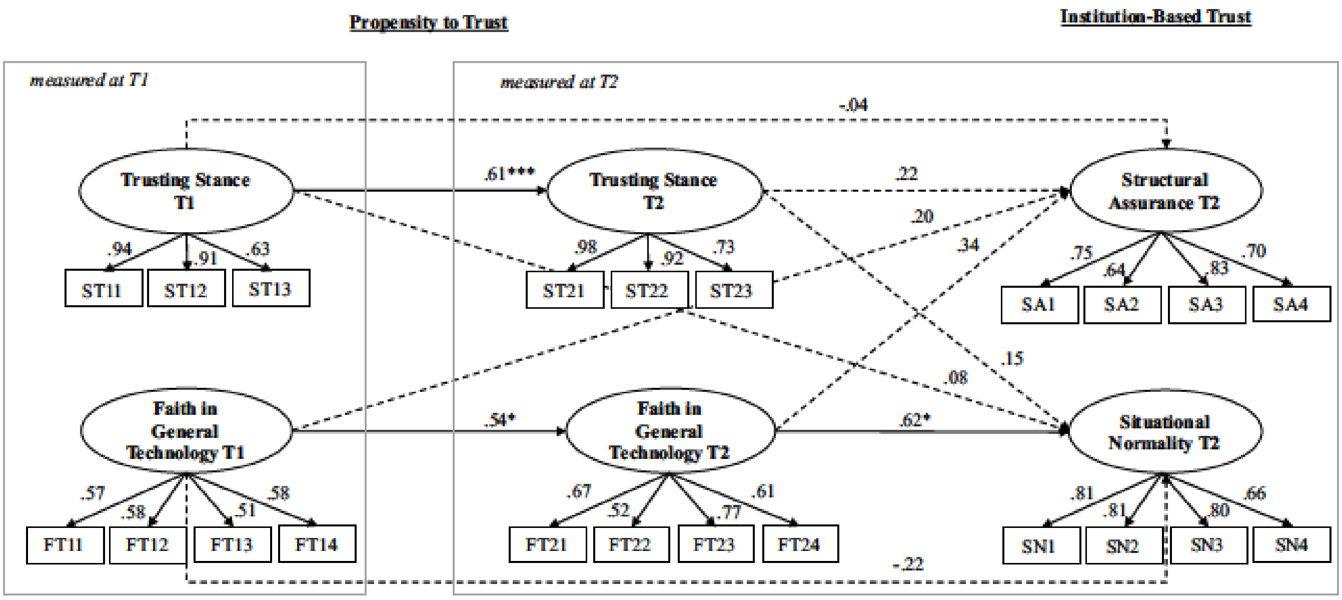


Figure 69. Results of the SEM conducted to test the longitudinal stability of trust in technology.

Paths from faith in general technology (T1) to faith in general technology (T2) and trusting stance (T1) to trusting stance (T2) were significant. However, the variables measured at T1 displayed no significant path to the other variables measured at T2. The path from faith in general technology (T2) to situational normality (T2) was significant, whereas the path from faith in general technology to structural assurance (T2) was not. Furthermore, the paths from trusting stance (T2) to both structural assurance (T2) and situational normality (T2) were not significant. A measurement of invariance across ET and ENT groups was not possible as the model did not converge. Similarly, the SEM analysis including the entire model of trust in technology (McKnight et al., 2011) conducted in Study A could not be replicated due to the low sample size of this study.

Table 26

Results of the CFA and SEM Conducted in this Study

	N	**χ^2**	***df***	***p***	**CFI**	**TLI**	**RMSEA [95%-CI]**	**SRMR**
<u>CFA</u>								
Propensity to trust T1	100	17.22	13	.190	.98	.97	.057 [.000;.121]	.049
Propensity to trust T2	100	14.49	13	.340	.99	.99	.037 [.000;.118]	.033
Institution-Based Trust T2	100	42.08	19	.002	.93	.89	.117 [.069;.165]	.048
Trusting beliefs T2	100	64.85	41	.010	.97	.96	.012 [.069;.165]	.065
<u>SEM</u>								
Longitudinal Model	100	346.79	197	< .001	.86	.84	.089 [.073;.104]	.089

Note. CFA, Confirmatory Factor Analysis; SEM, Structural Equation Modelling.

Discussion

It was the aim of Part 2 to examine longitudinal sequences in the trust in a specific technology model (McKnight et al., 2011), that had been applied to the field of fitness apps. Specifically, it was an aim to test the stability of propensity to trust in fitness app novices after six weeks' fitness app usage, and to test whether propensity to trust in fitness app novices influences the degree of institution-based trust measured after six weeks of fitness app usage. The trust in a specific technology questionnaire (McKnight et al., 2011) has been established and tested in the field of traditional computer programs (i.e., Excel) and has been shown to predict intention to explore and deep structure usage (McKnight et al., 2011). This study is the first testing this model in a longitudinal design.

In this study, the CFA analyses of each component of the model (i.e., propensity to trust measured at T1 and T2, institution-based trust measured at T2, and knowledge-based trust measured at T2), indicated good model fits. Therefore, good construct validity of the questionnaire was indicated. The findings of this study using a different sample are in line with the results found in Study A, contributing to further validation of the trust in a specific technology model applied to the fitness app context.

Regarding the main analysis using longitudinal data, it was hypothesized that propensity to trust is stable over time. It was found that trusting stance (T1) significantly affects trusting stance (T2), and that faith in general technology (T1) affects faith in general technology (T2). The results indicate that both trusting stance and faith in general technology are stable over a period of six weeks' time. Therefore, *Hypothesis 3a* was confirmed. Propensity to trust has been defined as a non-specific and relatively dynamic trait of the trustor, describing the willingness to rely on a technology across different technologies and situations (McKnight et al., 2011). Rotter (1967) defined trust as an enduring personality trait.

For example, a scale measuring interpersonal trust (Rotter, 1980) demonstrated good test-retest reliability after seven months. However, this assumption has not been tested in the field of fitness apps to date. In non-technology contexts, *general trust propensity* is regarded as a within-person attribute that refers to a person's general ability to trust (Gill et al., 2005; Mayer et al., 1995) and that has been found to be stable across situations and time (e.g., Alarcon et al., 2016, 2018).

With regards to causal relations within the model, the effect of propensity to trust on institution-based trust was tested. It was hypothesized that high levels of propensity to trust lead to higher levels of structural assurance measured six weeks later. In the SEM analyzing the longitudinal sequence of propensity to trust (T1) and propensity to trust (T2) on institution-based trust (T2), no sufficient model fit was indicated. Specifically, propensity to trust (T1) was unrelated to both scales of institution-based trust (T2). Also, in contrast to assumptions within the model, trusting stance (T2) was unrelated to institution-based trust (T2), and the faith in general technology scale (T2) was only related to the situational normality scale (T2). Although the item loadings displayed stable results that were consistent with the assumed model, the overall longitudinal validity of the model appears to be limited. Therefore, *Hypothesis 3b* was not confirmed, indicating that causal relations within the model of trust in a specific technology cannot be assumed. In contrast to the findings in this study, general trust propensity is assumed to influence both trust and its antecedents (Mayer et al., 1995). The propensity to trust is particularly of relevance when a new relationship begins and the trustor has no knowledge about and no former experience with the trustee, such as during adoption of fitness app usage (Colquitt et al., 2007; Mayer et al., 1995; McKnight & Chervany, 2001). Furthermore, propensity to trust has been identified as a predictor of perceived ability, benevolence, and integrity, however only in individuals having little direct experience with the trustee (Murphy, 2003). Using a longitudinal design, it was found that the propensity to trust can influence the initial perception of trustworthiness, but cannot predict the change in trustworthiness over time (Alarcon et al., 2016). However, it should be considered that previous research presented above has targeted *trusting beliefs* instead of *contextual assumptions* such as institution-based trust (McKnight et al., 2011). Therefore, the comparison between general trust research based on Mayer et al. (1995) on the one hand, and trust in a specific technology on the other hand could be of limited validity. Beyond this background, the effects of propensity to trust and institution-based trust on trusting beliefs would have been of interest. However, these relations could not be tested due to issues of model convergence.

Strengths and limitations. It was a strength of this study that the sample assessed in this study was analyzed under highly similar and controlled randomized conditions. Specifically, all participants were fitness app novices at the beginning (T1), used the same fitness app and gadget across time, and had similar experience referring to the time period and app functions when assessed during the post-test (T2). All participants were provided with identical fitness wearable devices that were connected to a fitness app on their smartphone device and were able to track their daily step count, the calories they had covered during the day, and the number of active minutes per day (at least 15 minutes of light activity). As Study C included an experimental manipulation, minor differences in the app functions were implemented. Whereas the ET group (n = 50) used a daily step target option (i.e., 10,000 steps per day), the ENT group (n = 50) did not use such a daily step target. Beyond this background, it was also of interest to analyze whether this difference in experimental conditions could have led to differences in propensity to trust, institution-based trust, and trusting beliefs across groups and time. To evaluate this question, it was the aim to conduct a supplementary analysis of invariance in addition to the SEM. However, the model did not converge due to the small sample size. Furthermore, it was not possible to assess institution-based trust in a sample of fitness app novices. Therefore, the longitudinal sequence between institution-based trust and trusting beliefs could not be tested in this study. Future studies could target the analysis of potential causal relations between institution-based trust and trusting beliefs.

This study was the first to test the trust in a specific technology model (McKnight et al., 2011) in a longitudinal design. In sum, the propensity to trust can be regarded as a broad and multi-faceted assumption about technology that is stable over six weeks' time of fitness app usage. Furthermore, propensity to trust represent relatively unspecific assumptions that affect more concrete and technology specific assumptions in a vertical, but not horizontal (i.e., longitudinal) manner, however with limitations. Future studies are needed to replicate the mixed findings with regards to associations between propensity to trust and institution-based trust, and to test potential causal relations between institution-based trust and trusting beliefs.

Overall, Study A and Study B had shed light into the process of initiation of, maintenance of, and dropout from fitness app usage, and additionally identifying the roles of risks (e.g., psychological risks) and benefits using trust in technology as key factors. The present Study C contributed to the understanding of causal relations and temporal stability within the model of trust in technology. Furthermore, the effects of self-tracking on psychological well-being and body and trust related aspects were targeted.

7. General Discussion

Facing increasing health risks associated with physical inactivity (e.g., WHO, 2017), fitness app usage has been identified as a promising tool to enhance physical activity in the broad population (e.g., Schoeppe et al., 2016). However, along with a range of benefits, fitness app usage has also been associated with certain risks (e.g., data insecurity; Barcena et al., 2014) and is associated with high dropout rates (GfK, 2017). Thus, to understand the role of trust in fitness app usage, three key questions were addressed throughout this work:

(1) How do *trust*, *risk,* and *benefit* perceptions contribute to understanding *fitness app usage*, including the processes of initiation, maintenance, and dropout?

(2) Can *body trusting* be regarded as a novel form of trust? How are *body trusting* and *trust in technology* related to each other and to *fitness app usage*?

(3) Can constant self-tracking *via fitness apps* change a person's *body trusting*?

To answer these questions, a heuristic research framework model (Figure 70) was established, in order to guide the steps and analyses of this work. The research framework model integrates the fields of communication technology usage, body and health related aspects, and trust research (i.e., risks and benefits). Looking at the overlaps between these interdisciplinary fields, it was the purpose to identify the interrelations and contributions of the three intersections, explicitly fitness app usage, trust in technology, and body trusting in this work.

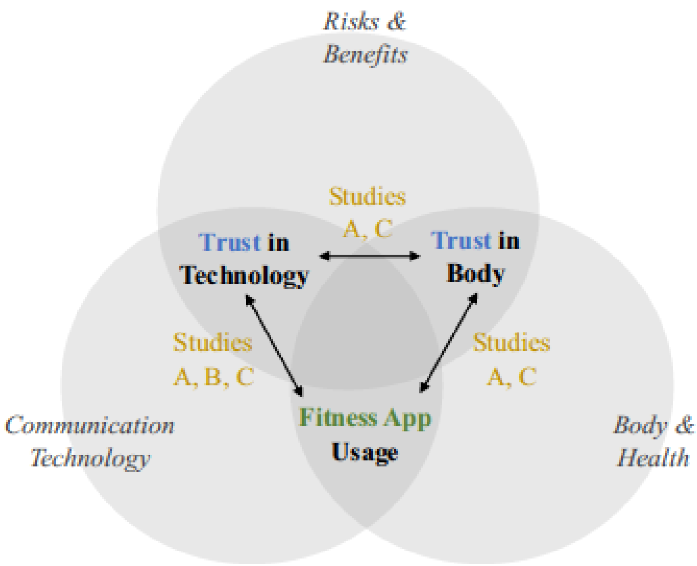


Figure 70. The research framework model proposed in Chapter 5 to identify the interrelations between fitness app usage, trust in technology, and body trusting.

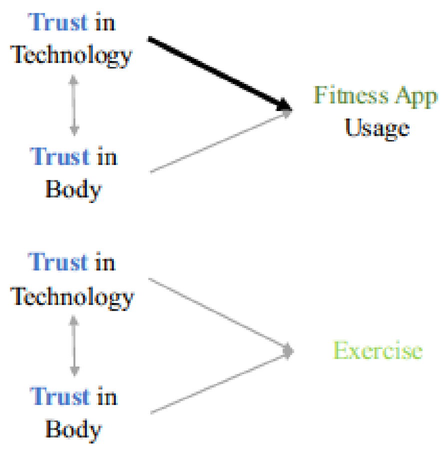
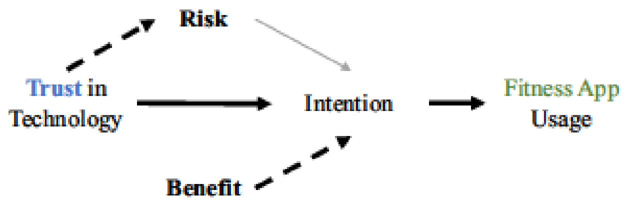
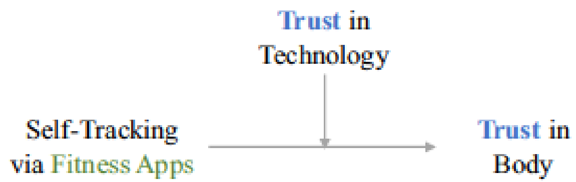
Overall, Chapter 1 was designed to provide a general introduction of the key aspects targeted in this work. Chapter 2, Chapter 3, and Chapter 4 provided insight into the theoretical foundation and previous research in the fields of digitalization, trust research, and self-tracking including body trusting. In Chapter 2 it was outlined how digitalization has changed our everyday lives and how digitalization has been applied to enhance health behavior and specifically physical activity via fitness apps. To explain the adoption and maintenance of technology, various approaches ranging from general technology to specific fitness app usage were presented. In brevity, fitness apps are a current trend and can be connected with wearable devices to track body related parameters such as the daily step count. Fitness app usage can be highly beneficial, for example to enhance physical activity and health behavior (e.g., Schoeppe et al., 2016), but can also entail risks, such as issues with data security (e.g., Barcena et al., 2014). When examining models that focus on approaching the prediction of technology usage, one model appears most prominently, namely the Technology Acceptance Model (TAM; Davis, 1989). The TAM has been established to explain why people accept or reject technology, and it has been used to explain early stages of technology usage. It integrates aspects of perceived benefits of a technology as predictors for technology acceptance and is rooted in the Theory of Reasoned Action (TRA; Ajzen & Fishbein, 1980). Chapter 3 provided a comprehensive presentation of the theoretical foundation of trust research, embracing different approaches to trust and aspects within the nomological framework of trust (e.g., objects of trust, trustworthiness, and the trustor). One useful basis to classify different aspects of trust is once again provided by the TRA which postulates a sequence explaining human behavior based on general attitudes, leading to intentions, and resulting in actual behavior. Furthermore, applications of trust research in a technology context were presented, including the establishment of the trust in a specific technology model (McKnight et al., 2011). This model is rooted in the prominent and most widely used integrative model of trust (Mayer et al., 1995). In summary, progress in media and digital communication underlie rapid changes, providing small starting points of experience and knowledge (e.g., Rosa & Scheuermann, 2010). Based on this, especially risk and benefit assessments have been identified as especially relevant factors to help understanding fitness app usage. To provide a more elaborate theoretical framework, newer models have integrated trust theory with aspects of the TRA that include benefit and risk assessments. These models were presented and identified as a pillar of research in this work. In Chapter 4, fitness app usage was presented as a form of practicing self-tracking, which has become popular within the *quantified self*-movement. Self-tracking via fitness apps has been described as a means to practice body trusting in previous works. Therefore, body trusting was defined and integrated into a theoretical framework of body awareness. In brevity, self-tracking and feedback provided by wearables has been identified as beneficial across diverse disciplines, such as healthcare or professional sports, and has been described as a form of biofeedback (e.g., Bechly et al., 2013; Gastin et al., 2013; Rouhani et al., 2012). People engaged in self-tracking hope to find patterns in their behavior, which has been suggested to reduce diverse risks (e.g., En & Pöll, 2014). Furthermore, self-tracking has been identified as a means to practice body awareness and body trusting (e.g., Sharon & Zandbergen, 2017). Chapter 5 provided a research program of this work postulating specific research questions. Chapter 6 entailed three studies and diverse analyses targeting these research questions. In the following, these results found in Chapter 6 will be targeted and summarized in a general discussion of this final Chapter 7. Chapter 7 provides implication for theory building and future research, this work's theoretical and methodological strengths and limitations, and practical applications that go beyond the specific discussions of the results that have already been provided in the discussion sections of Chapter 6.

Particularly, it is generally discussed if and how trust concepts can be applied to the technology context, how trust in technology can be applied to understand fitness app usage, and whether the model of trust in technology underlies causal relations throughout the sections 7.1-7.6. Also, the theoretical implications of the effects of self-tracking via fitness apps, and the general role of trust in body trusting are discussed beyond the background of the specific results found in this study. Furthermore, overall practice-relevant implications for safe and healthy fitness app usage are provided in section 7.7. Finally, the results of this work are integrated into the heuristic research framework model that guided through this work in the final section 7.8. An overview of the main research questions and the key results are summarized in Table 27.

Table 27

Overview of the Main Research Questions and Results

Study	Research Question	Main Result	Visualization
Study A	Part 1 Associations of fitness app usage with a broad range of variables; exploration of factors that are associated with dropout	Trust in technology is a key aspect in the initiation of, maintenance of, and dropout from fitness app usage.	Fitness App Usage
	Part 2 & 3 Application of the *Trust in a Specific Technology* model (McKnight et al., 2011) to the context of fitness apps via SEM and Analyses of Invariance	The trust in technology model can be applied to the fitness app context, however with limitations regarding institution-based trust. Propensity to trust can explain initiation of fitness app usage and trusting beliefs can explain maintenance of and dropout from fitness app usage.	**Trust** in Technology → Fitness App Usage
	Part 3 Prediction of the dropout from fitness app usage via Survival Analyses	The reliability and situational normality scales negatively predict dropout from fitness app usage, whereas the results of the helpfulness scale that positively predict dropout should be interpreted with care.	**Trust** in Technology → Fitness App Usage

	Part 3 Effects of congruence and incongruence among trust in technology and body trusting on fitness app usage and exercise via RSA	Neither congruence nor incongruence effects of trust in technology and body trusting on both fitness app usage and exercise exist. Body trusting is not related to trust in technology and is not related to fitness app usage. Therefore, the role of trust in body trusting remains vague.	
Study B	Extension of the model (trust predicts fitness app usage) by *perceived risk* and *perceived benefit* using a model proposed by Kim et al. (2008) via SEM	The model can be applied to the fitness app usage context, however with limitations. As indicated by the dashed lines, the application is specific to the dimensions of psychological and performance risks and benefits.	
Study C	Part 1 Effects of self-tracking via fitness apps including the implementation of an external step target on body trusting and the moderating role of trust in technology via Multilevel Bayesian Analysis	Both self-tracking via fitness apps and the implementation of an external step target do not lead to changes in body trusting, body listening, and psychological well-being after six weeks' fitness app usage. Trust in technology does not moderate this effect.	

Part 1 Examination of external validity of body trusting and a potential causality between body trusting and psychological well-being	Body trusting is associated with psychological well-being and leads to psychological well-being one day later, however not when controlling for body trusting in well-being.	**Trust** in Body → Psychological Well-Being
Part 2 Longitudinal analysis of the Trust in a Specific Technology Model (McKnight et al., 2011) via CFA and SEM	Propensity to trust is stable over six weeks' time. Causality within the model of trust in technology cannot be assumed in the context of fitness app usage.	**Trust** in Technology T1 → **Trust** in Technology T2

Note. Bold lines; significant associations were found; dashed lines; dimension specific associations were found; grey lines; no significant associations were found; CFA, Confirmatory Factor Analysis, SEM, Structural Equation Modelling, RSA, Response Surface Analysis.

7.1 Trust Applied to the Technology Context

It was a first aim of this work to apply trust theory to the digital context, and specifically to better understand fitness app usage. Therefore, the trust in a specific technology model (McKnight et al., 2011) was applied to the fitness app context. In doing so, it was also crucial to understand if traditional trust concepts can generally be applied to the digital context. In general, digitalization and the availability of technical devices such as smartphones have changed the way people work, live, and how they communicate with each other (e.g., Blöbaum, 2014; Latos et al., 2017). Digitalization provides the opportunity to gain large amounts of data within short times. This results in a complexity that requires abstraction of relevant and trustworthy information, raising the matter of trust. Also, digitalization facilitates access to knowledge and experience, and therefore can create transparency. Hence, users are provided with possibilities to control, and therefore to reduce risks. As indicated, transparent information can serve as a control system that bridges the difference between trust and risk by lowering the perceived risk (Schoorman et al., 2007).

Digitalization also changes the way people communicate with each other and it changes the relationships between persons, the public, and the media (Blöbaum, 2014; Fischer & Pöhler, 2018; Rosa & Scheuermann, 2010). Many people are permanently online and are connected with electronic devices (Vorderer & Kohring, 2013). For example, communication via the media has changed the way people rely when assessing the trustworthiness of a trustee or a trusted object. Cues to evaluate the trustworthiness in interpersonal relations (i.e., appearance, gesture) become obsolete. Hence, the assessment of trustworthiness in digital context changes and is rather based on reputation and expertise of internet news providers (Flanagin & Metzger, 2007). Beyond the background of multiple risks associated with technology usage that have been outlined throughout this work, new forms of trust emerge. In its traditional sense, trust was regarded as an interpersonal construct describing face-to-face interactions (Lewicki et al., 2006; Luhmann, 1968). In digital times, the traditional concept of interpersonal trust shifts from trust relations *between persons* to trust relations between persons *and the media*, such as computer programs or the smartphone (McKnight et al., 2011; Söllner et al., 2012). Therefore, it has been discussed whether digital media can be regarded as a communication partner and whether trust can be a relevant factor in such relationships.

On the one hand, an important distinction between human-technology and human-human interactions is that technology lacks intentionality and emotions (Lee & See, 2004). Whereas trust in humans often involves value and emotion-based features of loyalty and benevolence, trust in technology can only be based on previous experience. Interactions between humans vary in their degree of symmetry (Greenspan, Goldberg, Weimer, & Basso, 2000). However, human-technology communication completely lacks symmetry, leading to the question whether theories describing interpersonal communication can be transferred to the digital context.

On the other hand, research has indicated that human reactions to computers are comparable to their reactions to human interaction partners (Reeves & Nass, 1996). Specifically, it has been identified that technical devices such as computers, portable computers, and smartphones can function as social actors (Fogg, 2002; Green & Kreuter, 1991; West et al., 2012). As introduced in Chapter 2, Fogg (2002) stressed that computers include functions that reward people with positive feedback, model a target behavior or an attitude, and also provide social support (e.g., via social networks and social platforms). Health related apps include aspects that provide rewards, a feedback for behavior, and also enable the user to interact with others (e.g., friends and family, health professionals) via social networks and media (West et al., 2012). Rilling et al. (2002) found that human-computer interactions share neurological correlates with human-human interactions: When the computer responds to human behavior in a cooperate way, orbitofrontal cortex activation can be observed, which is also associated with activation after cooperative human-human interactions. However, the anteroventral striatum, which is also activated during human-human cooperation, is not activated during human-computer interaction. Further research indicates that users tend to accept software more if the software displays personality characteristics that are similar to the human user's characteristics (Nass & Lee, 2001). Also, software designs that stimulate affect are more likely to promote productivity and affect (Norman, Ortony, & Russell, 2003). With regards to specific perceptions of trustworthiness, it has been discussed that benevolence cannot be transferred to the digital context (Lee & See, 2014). However, Rasmussen, Pejtersen, and Goodstein (1994) argue that every technology is designed based on the designer's purpose and therefore also embodies a kind of intentionality of the designer. Furthermore, technologies become increasingly sophisticated and even adapt human characteristics, such as speech communication that is implemented in mobile phones or smart home systems (Nass & Lee, 2001).

Overall, it has been indicated that trust can successfully be applied to the technology context, and it has been shown to be an important indicator of human-technology interaction. These findings are present in both laboratory and naturalistic settings with regards to both machines, machine systems, and newer technologies such as computer programs and IT. For example, trust was found to predict decisions in a laboratory setting of a milk pasteurization plant (Muir & Moray, 1996), in driver's decisions based on in-car navigation systems (Fox & Boehm-Davis, 1998), in pilots' perceptions of automatic systems in the cockpit (Tenney, Rogers, & Pew, 1998), in usage of computer-based spreadsheet programs (McKnight et al., 2011), and in general IT usage (Söllner et al., 2012). In this work, trust in technology was identified as a key element in explaining fitness app usage. As outlined in the next section, trust in technology is a valuable aspect to explain the initiation of, maintenance of, and dropout from fitness app usage. Thus, the results of this work provide further support that trust in technology can be a valuable element in describing and explaining human-technology relations.

7.2 Trust in Technology and Fitness App Usage

Facing high dropout rates associated with fitness app usage, Study 1 provided a process-oriented and practice-relevant approach investigating differentiated aspects of trust in technology on different levels of usage. In Part 1, an exploration of factors associated with fitness app usage and dropout from fitness app usage was conducted. In both questionnaire-based and open format question analyses, trust was identified as a key aspect that can lead to better understanding of initiation of, maintenance of, and dropout from fitness app usage. Following the recommendations of McKnight et al. (2011), differentiated analyses across different stages of usage and subgroups (i.e., users, non-users, and dropout) were provided via two complimentary analyses throughout Part 2 and Part 3. High levels of propensity to trust led to higher levels of institution-based trust. Users reported higher levels of propensity to trust compared to non-users. The results indicate that propensity to trust can be measured across both users and non-users whereas the validity of institution-based trust is of limited value. Although objective risks related with data security are obvious (e.g., Barcena et al., 2014), the structural assurance scale appears to be a non-suitable tool to capture potential evaluations of trustworthiness in users and non-users. Furthermore, the results indicate that situational normality can contribute to explain longer durations of fitness app usage. With regards to trusting beliefs, functionality was found to be associated with longer duration of app usage. However, the means of all three scales reliability, functionality, and helpfulness were lower in dropout compared to users. In the survival analysis, functionality predicted a lower risk of dropout in fitness app usage, whereas helpfulness even predicted a higher risk of dropout. Although based on the same data set, the analyses conducted in Study A revealed different results about the connection between each aspect of trusting belief with duration of fitness app usage. These findings might be an artefact of the statistical method used in the analysis, or can imply that the importance of each trusting belief changes throughout the time of post-adoption, as implied by scholars across trust research (e.g., Lewicki et al., 2006; Mayer et al., 1995). Therefore, future studies should examine the development of trusting beliefs throughout the process of post-adaption in detail. When targeting the enhancement of the duration of fitness app usage and their practical implications, it should be considered that it is not yet clear for how long fitness app users should engage in fitness app usage to derive a benefit. For example, disengagement could also be an indicator of the successful adoption of a physical activity regimen. Future studies should focus on the examination of these questions in detail, preferably using longitudinal designs. Also, it can be of high interest to examine the process of initiation of, maintenance of, and dropout from fitness app usage in specific populations. For example, it can be highly relevant to focus on group-specific processes in physically inactive or overweight populations. Also, it can be of interest to identify specific circumstances, processes, and risks and benefits that are related to the application of wearable fitness app devices providing feedback for physically or also mentally diseased persons. In doing so, the treatment of diseases such as Parkinson's disease or hemiplegia could be improved (e.g., Shull et al., 2014), or increased activity across depressed persons might lead to improvements of symptoms. In the field of sport and exercise sciences, the examination of trust in fitness apps across the specific group of athletes and coaches has been demonstrated to be valuable (Querfurth-Böhnlein, 2018) and should be targeted in further studies. The results found in the RSA imply that body trusting and trust in technology are unrelated and that trusting is specific to the domain of relevance. However, the role of trust in body trusting stays unclear and should be targeted in future studies connecting body trusting with both outcome and other trust related variables (as indicated in the section 7.4 targeting body trusting below). In sum, results from Study A provided evidence for good construct and predictive validity of a German trust in fitness app questionnaire, and shed light onto the process of initiation of, maintenance of, and dropout from fitness app usage.

7.3 Trust, Risk, and Benefit

As progress in media and digital communication underlie rapid changes, only small starting points of experience and knowledge exist (e.g., Rosa & Scheuermann, 2010). Therefore, initial trust can be a key element in the explanation of initiation and maintenance associated with fitness app usage. The formation of initial trusting intentions and behavior are mainly guided by the assessment of costs and benefits (Lewicki & Bunker, 1996), and therefore, when examining initial trust in digital environments, the risk vs. benefit assessments are crucial factors to consider. Advancing previous studies in trust research, Study B was both a conceptual and practice-relevant work targeting the explanation of trusting intentions and trusting behavior in fitness app usage by including dimensions of perceived risk and benefit. The results found in Study B indicate that the model postulated by Kim et al. (2008) is a useful and valid framework to explain technology usage and intentions by trust, perceived benefit, and trust across different technologies by bringing together trust research and the well-established TAM (Davis et al., 1989). As implied in the model, trust is a highly relevant variable to explain intentions and actual behavior in the technology context and might contribute to the reduction of perceived risks. Therefore, the results support trust theoretical approaches postulating that trusting beliefs serve as a mechanism to reduce risk perceptions (e.g., Das & Teng, 2001; Lewicki & Bunker, 1996). However, longitudinal research is needed to test causal relations between trust, risk, and intentions. Furthermore, domain specific dimensions of risk and trust were identified that were associated with the intention to use a fitness app in this study: performance, psychological and overall benefit were associated with the intention to use a fitness app. Therefore, Study B underpins theoretical assumptions that risk and benefit can be regarded as dimensional constructs and that dimensions of risk vary in relevance across situations and contexts (Jacoby & Kaplan, 1972; Kaplan et al., 1974). In contrast to theoretical assumptions (e.g., Kim et al., 2008), risk was not associated with the intention to use a fitness app in Study B. However, these findings might be an artefact of the low perceived risk that was found to be associated with fitness app usage. To improve the understanding of the causal relations between trust and intentions and the general role of risk in theory building, future studies should be conducted using longitudinal designs.

7.4 Body Trusting

It was a further aim of this work to identify the role of trust in body trusting. Also, it was an aim to gain insight into the effects of self-tracking via fitness apps on body trusting and the relations between body trusting and well-being. With regards to the role of trust in body trusting, the results of the RSA conducted in Study A indicate that body trusting is not associated with exercise or with fitness app usage, implying little connection with other trust concepts or the domain of relevance. In traditional trust research, trust has been approached from different perspectives. From *psychology perspective*, trust is regarded as a state that lies within a person and is defined as a mental state or attitude (Castelfranchi & Falcone, 2010), i.e., as a state of willingness to make oneself vulnerable under risky conditions (Mayer et al., 1995). As identified in this work, fitness app usage can entail diverse risks, including health related risks that are evaluated by the trustor. Therefore, a trust conceptualization from psychological perspective might be compatible when regarding body trusting as a trust concept. However, from *sociology perspective*, trust has been described as a relation between the trustor and the trustee (the object of trust). Instead of a property within a person, trust is viewed as a social phenomenon and a property of collective units (Sztompka, 1999). As body trusting refers to an evaluation of the *own* body and displays neither relations to *external* objects nor persons, a conceptualization of body trusting as a trust concept would not be compatible with the sociology perspective on trust.

Overall, scholars across the disciplines agree that trust is based on perceptions and experiences in the past, and is oriented toward the future. These definitions of trust can be transferred to the context of trust in the own body as body trusting also refers to experiences in the past and is oriented toward the future (e.g., as body perceptions are used as information to guide future health behavior). Furthermore, trust is assumed to be easier to destroy than to build, refers to a situation, object, performance, or problem, and it is based on a free decision (Blöbaum, 2016; Lewicki et al., 2006; Mayer et al., 1995). Particularly, body trusting refers to an object—the own body—and is also based on a free decision. However, it has not yet been identified whether body trusting is easier to destroy than to build, leaving open questions at this point. Using the Theory of Reasoned Action (TRA; Ajzen & Fishbein, 1980) as a framework to understand aspects of trust, scholars introducing models of trust varied in defining trust as a belief, an attitude, an intention, or a concrete behavior. With regards to the specific items measuring body trusting, the three items represent aspects of (1) trustworthiness, (2) intention to trust, and (3) one item that could not clearly be integrated into a trust concept. Therefore, the set of items used to measure body trusting make it difficult to find a clear theoretical integration and to identify body trusting as an aspect of trust, as discussed in Study A. In sum, some specific attributes of traditional trust conceptualizations could be connected with body trusting, whereas some could not. Future research should examine body trusting beyond the background of diverse body related risks. Research should also focus on the trajectories of how and if body trusting can be built and destroyed to gain deeper insight into the nature of body trusting and the role of trust within body trusting.

In Study C, the effects of self-tracking via fitness apps on body trusting were examined. Digital media can provide a tool to produce “hard facts” (En & Pöll, 2016, p. 44).

Hence, self-tracking is described as a means to practice *control*. Controls (such as fitness apps) influence the evaluation of risk (Schoorman et al., 2007) and can bridge the difference between perceived risk and trust by reducing the perceived risk. However, the interrelations between diverse aspects of trust (i.e., trust in technology, body trusting), their interrelations with *actual* and *perceived* risks and *perceived* control are of complex nature. To approach the understanding of these interrelations, sophisticated experimental studies are needed that specifically target the manipulation of isolated aspects mentioned above. Additionally, future studies require a better understanding of the role of trust in body trusting to evaluate these more complex research questions.

Approaching the external validity of body trusting, potential causal relations between body trusting and well-being were explored via sophisticated multilevel Bayesian analysis in Study C. Here, a clear connection between body trusting and well-being was found, indicating the adaptive character of body trusting. Body trusting has been identified as a desired attribute in previous studies and can be enhanced via meditation training (Bornemann et al., 2015). However, when controlling for auto-correlation, well-being was unrelated to body trusting one day after, and body trusting was even slightly negatively related to well-being one day after. Therefore, the exact nature of this connection still remains uncertain and needs to be explored in further studies, potentially using even more complex designs.

In sum, specific attributes of trust could be connected with body trusting, whereas some could not. Furthermore, the lack of associations between body trusting and trust in technology, and the missing connection between body trusting and both exercise and fitness app usage imply that it is difficult to integrate body trusting into traditional trust research models. As body trusting has been targeted in few studies yet, future studies are required to gain an understanding of the validity of body trusting, its relations to risk and control, and the overall role of trust in body trusting.

7.5 Self-Tracking via Fitness Apps

Digital media offer opportunities to gain objective information about peoples' environment and about themselves (Crawford et al., 2015; Lupton, 2013; Millington, 2009). The availability of objective information has been discussed as a means to control risks and therefore to gain more trust (i.e., in the own body; Nafus & Sherman, 2014; Sharon & Zandbergen, 2017). Specifically, the information obtained from digital media can produce "truer truths" (En & Pöll, 2016, p. 44) than potentially biased and untrustworthy feelings and memory. By means of producing hard facts and numbers about our body, people can become experts of their bodies, and self-tracking can even become a central aspect of existence, as indicated by Crawford et al. (2015, p. 486): "*I measure, therefore I am*".

However, besides a large range of benefits associated with fitness app usage, risks associated with privacy and data safety have been identified (e.g., Barcena et al., 2014; Kaewkannate & Kim, 2016). Furthermore, recent work has targeted specific risks associated with fine-tuning and self-optimization. In this context, self-tracking via fitness apps might lead to a loss of accepting imperfection in human beings, and to striving for perfection, norms, and success (En & Pöll, 2016). Hence, instead of contributing to a person's health, self-tracking via fitness apps would rather result in increased anxiety across users (Lupton, 2013). Furthermore, self-tracking has been discussed to shape people's perception, for example by creating experiences that are not our own (En & Pöll, 2016).

Study C was designed to gain an understanding of the effects of fitness app usage and the implementation of a specific external step target on psychological well-being and aspects of self-reported body trusting, body listening, and psychological well-being. The results found in this study contribute to a small but growing body of research indicating that fitness app usage does neither positively nor negatively influence psychological well-being. Furthermore, self-tracking via digital media and the implementation of an external step target were not found to affect body trusting, body listening, and psychological well-being after six week's fitness app usage. Although self-tracking has been described as a means to practice body awareness, body knowledge, or body trusting across scholars (En & Pöll, 2016; Nafus & Sherman, 2014; Sharon & Zandbergen, 2017), these assumptions could not be supported in Study C. Also, trust in technology was not found to moderate this association. However, beyond the background of insignificant main effects, it would have been hard to detect significant moderator effects of trust in technology. Therefore, future studies are needed that examine a potentially moderating role of trust in technology on various effects of fitness app usage in longitudinal designs. Furthermore, a large variability in effects was observed, indicating that the effects of fitness app usage are highly individual. Considering this large variability, effects might underlie specific conditions that are to be identified in future studies.

7.6 Longitudinal Examination of Trust in Technology

Study C was also designed to understand the temporal stability of propensity to trust after six weeks' fitness app usage and to identify causal relations within the trust in technology model (McKnight et al., 2011). The results found in Study C imply that the propensity to trust can be regarded as a broad and multi-faceted assumption about technology that is stable over six weeks' fitness app usage. Furthermore, it was indicated that propensity to trust represents relatively unspecific assumptions that affect more concrete and technology specific assumptions in a vertical, but not horizontal (i.e., longitudinal) manner as propensity to trust was not related with institution-based trust measured six weeks later. Overall, the isolated components of propensity to trust, institution-based trust, and trusting beliefs demonstrated good model fits, indicating that the trust in technology is a robust tool to measure aspects of trust in fitness apps. However, causal relations between institution-based trust and trusting beliefs could not be tested as both could not be tested in the fitness app novices at the beginning of the study. Consequently, future studies are needed to replicate the mixed findings with regards to associations between propensity to trust and institution-based trust, and to test potential causal relations between institution-based trust and trusting beliefs. Furthermore, it is of interest whether the act of trust (i.e., fitness app usage) can influence trusting beliefs, as it has been indicated in the integrative model of trust (Mayer et al., 1995).

When targeting the stability of trust, it is important to consider differences in trust definitions. For example, Rotter (1967) defined trust as an enduring personality trait and introduced a scale measuring interpersonal trust (Rotter, 1980) that demonstrated good test-retest reliability after seven months. In contrast, Mayer et al. (1995) stressed that propensity to trust is relatively dynamic and includes a person's specific history of interactions. To assess a test-retest reliability, time intervals of one to two weeks are common and have been recommended (Polit, 2014). However, to evaluate and better understand the validity of propensity to trust in technology as a dynamic vs. trait-like construct, longitudinal designs with long-time test-retest periods are needed, potentially including more than six months' time, as also indicated by Polit (2014).

7.7 Practical Implications

Fitness apps are a current trend and have been implemented to enhance health behavior in the broad population (West et al., 2012). Across diverse studies, it has been indicated that fitness app usage can promote physical activity, diet, and sedentary behavior (e.g., Glynn et al., 2014; Goodyear et al., 2017; Schoeppe et al., 2016; Stawarz et al., 2015). Furthermore, digital devices deliver feedback, helping users to understand and potentially modify their behavior (Crawford et al., 2015). For example, in medical healthcare, wearable devices can be beneficial to evaluate and treat diverse diseases, such as Parkinson's disease, osteoarthritis, or hemiplegia (Shull et al., 2014), and have also been discussed as a means to practice bio-feedback (e.g., Bechly et al., 2013; Nanhoe-Mahabier et al., 2012). In sport and exercise sciences, wearables can be beneficial to analyze the athletes' movements, exercise routines, etc. to improve training outcomes (e.g., Ahmadi et al., 2009; Gastin et al., 2013; Kidman et al., 2016). Furthermore, people engage in self-tracking to find patterns in their behavior, find causes and trajectories of a disease or of unhealthy behavior (Moschel, 2013). Additionally, the media—and specifically health product providers—have contributed to the perception that self-tracking is of epistemic value and can enhance quality of life (e.g., Crawford et al., 2015).

In this work, the within-person attribute of propensity to trust was identified as an aspect that can be connected with the initiation of fitness app usage. Furthermore, trusting beliefs were associated with the maintenance of fitness app usage. The most pronounced effect was found for functionality beliefs associated with a fitness app. Supporting the beneficial effects of fitness app usage on physical activity, app developers might thus lay a focus on promoting a great range of specific app functions. These settings could be designed to satisfy diverse and individual user specific needs and preferences. For instance, a recreational runner might benefit from app functions complementing his or her exercise related preferences whereas a physically inactive person would benefit from other settings that better match their needs. Also, it has been emphasized that it is important to convey clear and comprehensive information about the technology's abilities and functions, thereby providing support and helpfulness (Lee & See, 2004). It has been underlined that especially contextual factors need to be considered when targeting the improvement of fitness app usage to ensure correct understanding and usage of the technology. Furthermore, cultural differences can be of importance when implementing specific app functions in a fitness app (Lee & See, 2004). Another finding of this study is that domain specific dimensions of benefits were identified that were associated with the intention to use a fitness app in this study. Explicitly, performance and psychological benefit were associated with the intention to use a fitness app. Thus, it might be beneficial to focus on these aspects when targeting the maintenance of fitness app usage. For example, it might be useful to promote a variety of self-concepts that can be associated with fitness app usage to foster psychological benefits. Furthermore, the self-concepts of fitness app users (e.g., as a sportive person, a playful person, an efficient or health-conscious person) might be outlined. With regards to performance benefits, the overall performance of the gadget could be improved (e.g., Dennison et al., 2013; Salzwedel et al., 2017).

However, desired fitness app functions such as detailed profiles of a running session often require access and usage of systems that reveal highly private data. Consequently, a tradeoff between privacy and functionality of a fitness app exists. This risk is especially problematic when users are not aware of being tracked. This point leads to the consideration that self-tracking via fitness apps can also entail certain risks. For example, multiple risks of data security such as insecure gadget-cloud communication, data theft, third party misuse (e.g., advertisers, health insurances), or insecure cloud storage have been identified in the context of fitness apps (Barcena et al., 2014; Huckvale et al., 2015; Lupton, 2013). For example, individuals can be identified as being at risk of ill health by service providers such as insurance companies. Consequently, these persons could be refused from specific insurances, employment, or would be forced to pay higher insurance fees (Lupton, 2014). Furthermore, systematic measurement biases and unreliable measurement have been identified across selected devices and device functions (e.g., Gorny et al., 2017; Kaewkannate & Kim, 2016). To reduce potential risks and to provide healthy and safe fitness app usage, specific recommendations for both users and app developers referring to self-tracking apps have been provided (e.g., Barcena et al., 2014). For example, users should implement safe passwords, avoid sharing location details, and should carefully use sharing functions and social media. App developers and service providers should require strong passwords, make security testing, use secure protocols, and exclusively collect data that is required to provide a specific service. To ensure safe, unbiased, and high-quality content of health apps, it has been recommended to externally peer-review health apps by professionals (Mosemghvdlishvili & Jansz, 2013). For this purpose, particular guidelines have been provided by the US Food and Drug Administration (Krieger, 2013).

Also, self-tracking via fitness apps has been discussed to render norms and expectations about healthy behavior that convey fear and might even lead to obsessive self-surveillance (Lupton, 2013, 2014), however lacking of empirical foundation to date. Furthermore, fitness app usage can pose actual risks to specific user groups. As indicated in previous studies, self-tracking, and especially usage of calorie tracking functions can foster symptoms in persons who are prone to disordered eating (e.g., Eikey & Reddy, 2017; Simpson & Mazzeo, 2017). Therefore, these apps should not be recommended to specific groups of persons in order to protect them from the manifestation or aggravation of clinical symptoms. In sum, both overarching benefits but also risks of fitness app usage were identified that can be prevalent for all users, for users of specific apps or app functions, or for specific groups of app users. Thus, based on the results found in this work, specific recommendations were provided to enhance safe and healthy fitness app usage.

7.8 The Present Research Framework Model

In this work, a heuristic research framework model was established that guided through the areas of study and the analyses of this work (Figure 71). The research framework model entails the three fields of communication technology usage, body and health, and risks and benefits (i.e., raising the matter of trust). Synergizing these three fields, areas of overlap were identified, i.e., *fitness app usage*, *trust in technology*, and *trust in the body*. It was an overarching aim of this work to understand the associations and interrelations between these three aspects to provide practice-relevant implications for healthy fitness app usage and for theory building in the interdisciplinary fields of trust research, technology usage, and health and exercise sciences. The research model introduced in this work is a heuristic model that was established to provide a framework that guided through the present work. Particularly, this model served to shed light onto the processes between constructs that are rooted in diverse theories and multiple fields of research. Thus, this heuristic model does not claim to represent a novel theory, but rather serves as a heuristic approach to systematically examine the interrelations between trust in technology, body trusting, and fitness app usage from an interdisciplinary perspective.

Based on the evidence found in this work, it can be concluded that trust in technology is a key element in understanding the initiation of, maintenance of, and dropout from fitness app usage. Therefore, a connection from *trust in technology* to *fitness app usage* in the framework model can be confirmed, as indicated by a bold arrow in the model. However, the results of this work imply that relations between *body trusting* and both *trust in technology* and *fitness app usage* cannot be assumed, as indicated by the grey lines. Also, this work provided a first insight into the role of trust in body trusting, indicating that it is hard to integrate body trusting in traditional trust concepts.

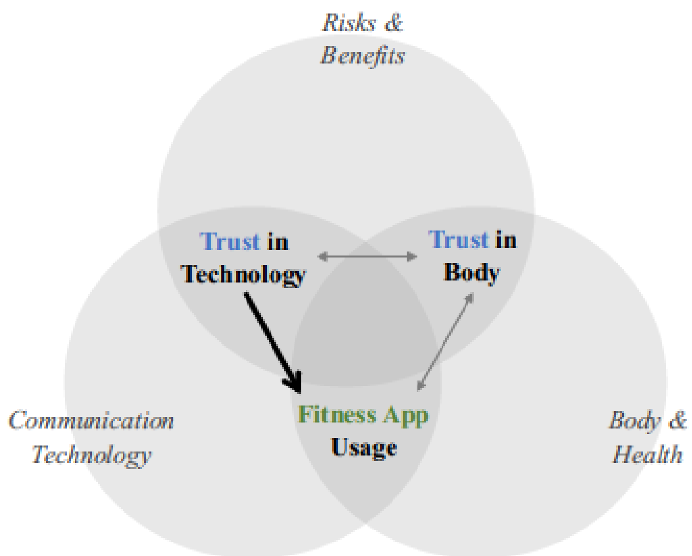


Figure 71. The research framework model integrating the results found in this work, identifying the interrelations between fitness app usage, trust in technology, and body trusting.

8. Conclusion

In this work, an interdisciplinary research framework model was established that integrated the fields of communication technology, trust research, and body and health related aspects. In particular, the intersections between these disciplines were examined, i.e., the relations between fitness app usage, trust in technology, and body trusting. In sum, this work provided a strong and manifold body of evidence that trust in technology is a key element in understanding the processes of initiation of, maintenance of, and dropout from fitness app usage beyond the background of diverse risks and benefits. Specifically, propensity to trust was identified as stable across six weeks' time and can be relevant in the initiation of fitness app usage. The examination of institution-based trust indicated limitations in validity. Trusting beliefs were found to be relevant in the maintenance of and dropout from fitness app usage, with a special focus on functionality beliefs. Further examination of risks and benefits indicated that dimension specific benefits are relevant in the intention to use a fitness app, i.e., with regards to psychological and performance benefits. The results also indicated that trust influences risk perception, while perceived risks are not associated with the intention to use a fitness app. Overall, specific recommendations for safe and healthy fitness app usage were provided.

Also, the role of body trusting was targeted in this work and was regarded beyond the background of trust research. Body trusting was neither related to trust in technology nor was it associated with fitness app usage or change after six weeks' self-tracking via fitness apps. Although body trusting refers to body related aspects of trustworthiness, trust, and risks, it seems difficult to integrate body trusting with traditional trust theories.

Examining the effects of self-tracking via fitness app (i.e., objective feedback) and the implementation of an external step target, no effects on body trusting, body listening, and psychological well-being were observed. Beyond the background of multiple risks and benefits associated with fitness app usage, the results imply that fitness app usage neither contributes to improvements in psychological well-being nor does it harm psychological well-being. However, considering the large variability in effects, future studies are needed to elaborate on potential influencing factors.

This work provided an application of diverse and sophisticated methodologies in an interdisciplinary research and was the first to shed light onto the processes of initiation of, maintenance of, and dropout of fitness app usage beyond the background of trust research, and to extend models of traditional trust research by integrating aspects of dimensional risk and benefit. This work was the first to connect body trusting with trust research, to examine the effects of self-tracking via fitness app usage on body trusting and body listening, and to examine causal relations between body trusting and psychological well-being. Thus, across the three studies conducted throughout this work, trust was applied as a predictor variable, an outcome variable, and as a moderator variable, providing comprehensive and manifold insights into the applications of trust research. Finally, practice-relevant implications were provided, including implications for theory building in the interdisciplinary fields of trust research, technology usage, and health and exercise sciences.

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10. Supplements

Supplement A

Supplementary Material to Study C

Supplement A

Supplementary Material to Study C

Table 1

Correlation Matrix of All Continuous Variables Assessed

	Body Listening	Body Trusting	Well-Being	Trusting Stance	Physical Activity	BMI	Age
Body Listening	**.69**	.38	.15	–.30	.14	–.19	–.07
Body Trusting	.32	**.62**	.26	–.06	.04	–.09	–.14
Well-Being	.15	.22	**.32**	–.12	.10	.03	–.07
Trusting Stance	-	-	-	-	–.10	–.09	.05
Physical Activity	-	-	-	-	-	.02	–.04
BMI	-	-	-	-	-	-	.23

Note. The correlations of the pre-test are presented above the diagonal; the correlations of the post-test are presented below the diagonal; the correlations of each variable between pre- and post-test are presented in bold on the diagonal. Trusting Stance, Physical Activity, BMI, and Age were assessed in the pre-test.

Table 2

Outcome Variables Measured in the Post-Test

	Group 1 (*n* = 49)		**Group 2 (*n* = 48)**		**Group 3 (*n* = 47)**	
	M	***SD***	***M***	***SD***	***M***	***SD***
Body Listening	3.93	0.82	3.71	0.69	3.96	0.90
Body Trusting	4.79	0.67	4.54	0.81	4.82	0.78
Well-Being	3.89	0.79	3.69	0.94	4.03	0.94

Note. Body Listening, Body Trusting, and Well-Being were rated on a 6-point Likert scale.

Table 3

Results of the Multilevel Analyses of Well-Being, Body Listening, and Body Trusting across Persons Comparing the Experimental Groups

	Daily measurement				**Pre-post measurement**			
	b	**95%-CI**	***SD***	**95%-CI**	***b***	**95%-CI**	***SD***	**95%-CI**
Well-being								
Intercept[a]	-	-	0.62	[0.50, 0.75]	-	-	0.88	[0.70, 1.09]
Time	0.24	[–0.04, 0.49]	0.80	[0.61, 1.02]	0.04	[–0.32, 0.42]	1.13	[0.88, 1.39]
ET Group	0.22	[–0.07, 0.50]			0.06	[–0.32, 0.45]		
Time:ET	–0.12	[–0.53, 0.28]			0.15	[–0.38, 0.66]		
Body Listening								
Intercept[a]	-	-	0.61	[0.49, 0.74]	-	-	1.19	[0.90, 1.55]
Time	0.09	[–0.12, 0.29]	0.48	[0.32, 0.65]	0.14	[–0.16, 0.44]	0.27	[0.01, 0.62]
ET Group	**0.38**	**[0.09, 0.67]**			0.18	[–0.37, 0.75]		
Time:ET	–0.13	[–0.43, 0.16]			0.23	[–0.22, 0.69]		
Body Trusting								
Intercept[a]	-	-	0.68	[0.55, 0.84]	-	-	1.20	[0.88, 1.56]
Time	0.13	[–0.10, 0.36]	0.60	[0.44, 0.80]	–0.11	[–0.43, 0.21]	0.59	[0.12, 0.99]
ET Group	**0.35**	**[0.05, 0.65]**			–0.01	[–0.56, 0.57]		
Time:ET	–0.23	[–0.57, 0.12]			0.45	[–0.01, 0.93]		

Note. *b* = mean regression coefficient across persons; $SD_{subjects}$ = standard deviation of the regression coefficient across persons; 95%-CI = 95%-credibility interval; regression coefficients whose credibility intervals do not include 0 are highlighted in bold.

[a] Since ordinal models have multiple intercepts, we do not report them for brevity.

Table 4

Latent Outcome Variability Compared Across Groups and Time Comparing ET and ENT Groups

	Daily measurement				**Pre-post measurement**			
	First Day		**Last Day**		**Pre-Test**		**Post-Test**	
	σ	**95%-CI**	***σ***	**95%-CI**	***σ***	**95%-CI**	***σ***	**95%-CI**
Well-being								
ENT Group[a]	1	-	0.89	[0.77, 1.02]	1	-	1.05	[0.88, 1.25]
ET Group	1.09	[0.97, 1.21]	**0.89**	**[0.79, 0.99]**	0.99	[0.82, 1.16]	0.97	[0.82, 1.15]
Body Listening								
ENT Group[a]	1	-	**0.83**	**[0.72, 0.95]**			0.97	[0.77, 1.21]
ET Group	1.05	[0.94, 1.16]	**0.79**	**[0.70, 0.88]**	1.12	[0.91, 1.36]	1.04	[0.83, 1.28]
Body Trusting								
ENT Group[a]	1	-	**0.76**	**[0.66, 0.88]**	1	-	1.03	[0.79, 1.33]
ET Group	1.03	[0.91, 1.15]	**0.81**	**[0.72, 0.91]**	**1.28**	**[1.01, 1.59]**	1.31	[1.03, 1.65]

Note. σ: latent standard deviation obtained from ordinal models varying across time and groups; 95%-CI: 95%-credibility interval of σ; standard deviations whose credibility intervals do not include 1 are highlighted in bold.

[a] The residual standard deviation of the ENT measured in the pre-test is fixed to 1 for reasons of identifiability.

11. Statements

11.1 Declaration Referring to the Own Contribution in this Work

The overall work

I, Lena Maren Busch, conceptualized and prepared all Chapters included in this thesis. All Chapters represent my own work and writing.

Chapter 6: Empirical Studies

Chapter 6 includes three empirical studies. All written work throughout Chapter 6 represents my own. Still, the studies were conducted with the help of diverse persons. The contribution of each person is outlined in the following.

Study A. I, Lena Maren Busch, conceptualized and led the study throughout the whole process. I developed the research design, conducted and managed the data acquisition, was responsible for the ethical approval and conduction of the trial, and the statistical analysis. The development of the research design was supported by Till Utesch, Linda Schücker, and Bernd Strauss. Till Utesch provided support with the data analysis. Sydney Querfurth-Böhnlein assisted in the development of the research design and used parts of the data collected in this study for a separate analysis in her dissertation thesis.

Study B. I, Lena Maren Busch, conceptualized and led the study throughout the whole process. I developed the research design, conducted and managed the data acquisition, was responsible for the ethical approval and conduction of the trial, and the statistical analysis. The development of the research design was supported by Anja Schmitt, Till Utesch and Bernd Strauss.

Study C. I, Lena Maren Busch, conceptualized and led the study throughout the whole process. I developed the research design, conducted and managed the data acquisition, was responsible for the ethical approval and conduction of the trial, and the statistical analysis. The development of the research design of Part 1 was supported by Till Utesch, Paul-Christian Bürkner, Bernd Strauss, and Katharina Geukes. Paul-Christian Bürkner and Till

Utesch provided support with the data analysis. Christin Resing, Laura Vieten, Alexandra Geier, and Franziska Sieber assisted with the data acquisition and data management. Christin Resing used parts of the data collected in this study for a separate analysis in her master's thesis. A preliminary draft of the results of Part 1 of Study C is available as a preprint. The online link to this modified preprint is provided in the introduction section of Study C.

Münster, 12th June 2019 ________________________

Lena Maren Busch

11.2 Personal Statements

Hereby I, Lena Maren Busch, declare that I have myself conducted the work on the submitted thesis, and that I have conducted the work without any unauthorized assistance. I have specified all sources used for this dissertation and any means of assistance, and I have not submitted this thesis in this or any other form as a thesis elsewhere for the purposes of examination.

Münster, 12th June 2019 ________________________

Lena Maren Busch

Hereby I declare that I have not been convicted of any crime relating to the misuse of my academic qualifications (§ 6 (3) of the Doctoral Regulations).

Münster, 12th June 2019 ________________________

Lena Maren Busch

Hereby I declare that I have not attempted to obtain a doctorate prior to this current attempt.

Münster, 12th June 2019 ________________________

Lena Maren Busch

Hereby I declare that this is not a cumulative dissertation according to § 7 (3) of the Doctoral Regulations. This dissertation does not contain any copyrighted material.

Münster, 12th June 2019 ________________________

Lena Maren Busch

12. Curriculum Vitae