Risk Perception & Personality Characteristics as Determinants in the use of mHealth Technology in the Context of Personal Fitness

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Risk Perception & Personality Characteristics as Factors towards the use of mHealth Technology in the Context of Personal Fitness

Abstract

Background: Insufficient physical activity among young adults (18-35) is a worldwide concern with little progress to improve. Despite public health promotion efforts sedentary behavior increases over the years in high-income countries from 32% to 37% and remains stable in low-income countries 16%. To promote physical activity several public health organizations have established physical activity guidelines that recommend engaging 150 minutes of weekly moderate-intensity physical activity to maintain a healthy lifestyle. However, according to a national study of the German population, only 44% of males and 35% of females meet these recommendations. Given their constant availability, motivational and supporting features interventions utilizing smartwatches started to emerge. However, smartwatches collect very private and sensitive information, which evokes various concerns in individuals and impedes adoption of smartwatches. Another factor that should be considered when it comes to the adaption of technology is personality. Therefore, this study aims to explore which risk perception factors (*privacy risk, performance risk, legal concern, trust and willingness to share personal data*) and which personality types *(agreeableness, emotional instability, extraversion, openness to new experience, conscientiousness)* are associated with adoption intention of smartwatches for personal fitness of young adults.

Methods: A cross-sectional online survey design was conducted with young adults (18-35 years) using two questionnaires (1) the Risk Perception and Adoption Intention of Smartwatches questionnaire and (2) the BIF-2-S questionnaire. A univariate analysis was accomplished to select variables to include in further analysis followed by a multiple linear regression analysis.

Results: The sample consist of N = 101 participants (51% male; mean (*SD*) age 25 (5.1) years). Most respondents have German nationality (89%) and do not use smartwatches (60%). The multiple linear regression analysis of the variable’s *privacy risk, trust and extraversion* with adoption intention indicated to explain 20% of the variance in adoption intention ($R^2 = .20$, $F\ (3, 46) = 7.95$, $p = .000$). Trust had a positive significant relationship with adoption intention whereas privacy risk and extraversion had a negative significant relationship with adoption intention.

Conclusion: Although the concept's privacy risk, trust and extraversion explain only 20% of the adoption intention it can be concluded that these concepts are still relevant and should be considered in the development of mHealth technologies for physical fitness. Based on the findings in this study smartwatch designers should consider to decrease individual's privacy concerns of smartwatches and with that increase individual's trust. As privacy risk is found to have a negative association with adoption intention and trust has a positive association, it could increase individuals' adoption intention of smartwatches. Besides that, integrating personality differences in the design can be effective to increase the adoption intention of specific groups of individuals. For instance, by including social comparison, competition, or other social features smartwatches might become more appealing for extraverts are would be more likely to be used for personal fitness.

Keywords: physical activity, young adults, mHealth technology, personality, personal fitness

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Introduction

Personal Fitness and persuasive technology

Despite significant public health promotion efforts, insufficient physical activity among young adults (18-35) is a worldwide concern as it is a major cause of obesity and the fourth leading factor for mortality (Guthold et al., 2018). The Healthy People review from the National Center for Health Statistic and the Center for Disease Control and Prevention (2010) indicate that approximately 65% of high school students engage in regular vigorous activity, compared to 32% of 18- to 24-year-olds and 23% of adults in the U.S. Similarly, German studies indicate that the physical activity level increases until the age of 13, and then decreases in the higher classes (Schmidt et al., 2017). As research suggests that the most decline in physical activity can be observed from adolescents to adulthood it is especially important to focus on the age group of young adults when it comes to promoting physical activity. To support individuals to be more active, several public health organizations have established physical activity guidelines. The Center for Disease Control and Prevention recommend 150 minutes of weekly moderate-intensity physical activity to maintain a healthy lifestyle (Center for Disease Control and Prevention, 2011). Individuals will benefit from improved cardiorespiratory and muscular fitness, bone health, reduce risk of cancer, type II diabetes and depression (World Health Organization, 2020). However, according to a national study of the German population, only 44% of males and 35% of females meet these recommendations (Krug et al., 2013). Therefore, to promote physical activity behavioral scientists and physical activity professionals face nowadays two major challenges: “how to get inactive people to initiate physical activity, and how to get irregularly active people to become active on a regular basis” (Nahas, & Goldfine, 2003). To give an answer to this question, evidence-based behavior change techniques should be discussed.

BCTs are designed to help developers of interventions to identify and apply evidence-based techniques to reach behavior change (Normand, 2008). Based on different studies it was concluded that the techniques: goal setting, self-monitoring and feedback are effective to promote behavior change especially in the physical activity context (Michie et al., 2011; Sniehotta, et al., 2005).Therefore, interventions that support individuals to (1) identify and set clear goals, (2) enable individuals to monitor their progress and lastly (3) give feedback on performance are especially successful to change individuals' behavior. In fact, the first step towards changing behavior is defining clear goals. Setting clear goals helps individuals to organize their behavior into practical and manageable steps to reach the goal (Normand, 2008). Moreover, goal setting encourages individuals to make a behavioral resolution and thus actively decide to change their behavior or maintain the change (Michie et al., 2011). Conn et al. (2014) reviewed interventions aiming to increase physical activity and found that goal setting is the third most often used technique to promote behavior change. However, forming goals alone is rarely sufficient to change behavior where other techniques such as self-monitoring and feedback on performance are important (Schachter, 2006). Self-monitoring is a technique that influences behavior by observing their own performance (Schachter, 2006). Examples of self-monitoring include observing behavioral performance, reflecting whether the performance was successful or not and develop behavioral consequences (Bandura, 1998). Michie et al. (2011) found that self-monitoring in combination with at least one other technique (e.g., goal setting) was related to the effectiveness of interventions to enhance physical activity. Lastly, feedback on performance is defined as a regulatory mechanism where the effect of an action is fed back to modify and improve future action (Ramani et al., 2019). One example of that technique is for instance identifying a discrepancy between the actual behavioral performance and a goal (Michie et al., 2011). Based on the already established effectiveness of these BCT various interventions were developed. Given the popularity of the internet technological interventions using these BCT's started to emerge. One example of such technological interventions is eHealth.

eHealth is defined as " the use of information and communication technology, especially the internet, to improve or enable health and health care" (Eng, 2011). Based on this idea, mobile health (mHealth) technologies were developed entailing the BCT's goal-setting, self-monitoring and feedback on performance to improve individuals' physical activity. One example of such mHealth technologies are smartwatches. Smartwatches are described as computerized software devices that continuously monitor users' physical activity (e.g., steps, calories) and physiological data (e.g., heart rate, skin temperature) and can communicate with the user throughout the day (Oncescu et al., 2014). Activity trackers such as smartwatches are an emerging solution for motivating people to reduce sedentary behavior. Smartwatches can be used by a wide array of people ranging from adolescents to older adults (Oncescu et al., 2014). Moreover, smartwatches are constantly available to their users', measuring health data 24/7 (Oncescu et al., 2014). Therefore, it enables the users for continuous self-monitoring and feedback on performance whenever they wish for. Besides that, individuals can also set daily goals as for instance define the number of steps they want to achieve. Lyons et al. (2014) assessed the effectiveness of the BCT's in wearable activity trackers and found that all trackers helped users to self-monitor behavior, obtain feedback and generally support users in goal setting. However, to ensure that smartwatches will be used by individuals' and persuade them to engage in physical activity it is important to design smartwatches engaging and persuasive.

The PSD model provides a guide for designers, on what should be considered during the design of technology to reach behavior change (Oinas-Kukkonen, & Harjumaa, 2009). Persuasion is described as a means of communication with the aim of changing or modifying the beliefs, values, attitudes or behavior without deception (Guerini et al., 2007). The persuasion can occur based on different strategies: primary task support, dialogue support, system credibility, and social support (Oinas-Kukkonen, & Harjumaa, 2009). Primary task support includes factors that support the carrying out of the goal behavior as for instance becoming more active (primary task). For instance, by monitoring the progress individuals can compare their actual activity level with their desired level and thus be motivated to reach their goals (Wan, & Zhang, 2020). Dialogue support refers to the design principles related to human-technology dialogue that helps users to achieve their goal. One example of dialogue support is providing the users with feedback or reminders to engage in physical activity. System credibility support strategy aims to persuade the user with a credible system that provides for instance reliable health information . Lastly, the social support strategy utilizes social influence (e.g., social comparison) to make the system more motivating for the users (Wan, & Zhang, 2020). In fact, a technology that is designed persuasive is more effective in terms of behavior change and maintenance (Guerini et al., 2007). However, despite the (1) evidence-based behavior-change techniques which are integrated into the (2) constantly available technology with a (3) persuasive design, the physical activity of individuals does not significantly improve. Therefore, factors should be assessed which are related to individuals' adoption intention of smartwatches.

Risk Factors by Using Smartwatches

In fact, research shows also a 'dark side' of smartwatches, with risk factors influencing the adoption intention (Barcena et al., 2014). In the context of smartwatches, the term "risk" can be understood as: the perception of uncertainty in the use of smartwatches and their severity in terms of consequences (Khedmatgozar, & Shahnazi, 2018). Studies indicate that besides all advantages of smartwatches, individuals are still concerned about the risks (Barcena et al., 2014; Deng et al., 2018; Featherman, & Pavlou, 2003; Gao, & Bai, 2014). Research identified five different categories of risk factors that might influence the adoption intention of smartwatches: (1) privacy risk, (2) performance risk, (3) legal concern, (4) trust and (5) willingness to share personal data (Barcena et al., 2014; Deng et al., 2018; Featherman, & Pavlou, 2003; Gao, & Bai, 2014).

Privacy is one of the factors that individuals are concerned about when using smartwatches. The term privacy is defined as: "the claim of individuals ... to determine for themselves when, how, and to what extent information about them is communicated to others" (Jackson, & Westin, 1968). Since smartwatches are designed as very personal devices which measure private information like health data, sleep quality and even GPS information the main risk of smartwatches is to lose control over the collected personal information. Smith et al. (2011) indicated that consumers are concerned about their privacy and especially about the unclear distribution of data and its use by third parties. In fact, third parties could intercept the data during transmission from the smartwatch to the connected smartphone or even gain access to the data stored in the connected smartphone (Barcena et al., 2014). Therefore, it can be stated that there is a threat that cybercriminals can hack the smartwatch or the connected mobile phone and exploit the sensitive information for their own purpose. Moreover, consumers are not aware of how the information is collected during service time and how that information will be stored (Porambage et al., 2016). Therefore, it can be stated that privacy imposes a great threat to the adoption intention of smartwatches since individuals will take all the above-mentioned risks into account when deciding to buy and consequently adopt smartwatches in their daily life's.

Research reports that individuals are also concerned about the performance of smartwatches. Performance risk can be understood as the risk that the product could malfunction and not performing as it was designed and therefore failing to deliver the desired benefits (Grewal et al., 1994). Since products with low performance are more likely to be abandoned, cause frustration, and do not function according to the way a user thinks they should, they could impose a great risk to individuals' adoption intention (Kortum, & Peres, 2014). Further, due to a low-performance smartwatch can suffer losses in reputation and brand loyalty from its users which might cause further disuse and affect the adoption intention as well (Jokela, 2004). For individuals to believe that using a smartwatch will enhance their self-efficacy to be more active, users need first to believe that the information is trustworthy, thus being valid and reliable (Preusse et al., 2014). Based on previous research it can be stated that the performance risk of smartwatches can have a negative influence on the adoption intention.

Next, legal concern is described as "a rule of conduct or action prescribed or formally recognized as binding or enforced by a controlling authority" (Brown, & Adams, 2007). In other words, it described users' concerns that their health information and privacy protection is not safeguarded by law when using smartwatches. In fact, all current regulations cannot effectively limit and regulate the processing of personal health information by smartwatch companies or any third parties (Minbaleev et al., 2020). Moreover, it can be claimed that overall, regulations and laws play a passive role in relation to emerging technologies (Minbaleev et al., 2020). This happens because it is very difficult to predict the modification of certain technologies or their appearance in general. Since it is already clear that individuals are concerned about their privacy when using smartwatches and research found that these concerns undermine individuals' adoption intention of smartwatches, the concept legal concerns might have an influence on adoption intention as well.

Trust is one major factor that makes individuals use eHealth technologies despite all risks and uncertainties (AlHogail, 2018). Trust refers to: "users' willingness to believe and implement the advice or information acquired through mHealth services" (Doney et al., 1998). Deng et al. (2018) researched the adoption intention of mHealth services and found that individuals' beliefs about technology can influence their attitudes towards that technology and affect further adoption. Deng et al. (2018) concluded that individuals trust in mHealth technologies helps to decrease individuals concerns about that technology which in turn has a positive effect on the adoption intention. Tu (2018) research adoption intention of Internet of Things (objects which are embedded with sensors, software, and other technologies for the purpose of connecting and exchanging data with other devices over the internet) (Ashton, 2009) and supported these findings. It was found that the reduction of the uncertainty factors (risks, fears) increases the trustworthiness of IoT and consequently enhanced the intention to adopt IoT technology (Tu, 2018). Similarly, Gao and Bai (2014) researched the adoption intention of healthcare wearables and showed significant effects of trust on the intention to adopt technology. Based on this finding it can be suggested that trust is a significant influencer of the adopt intention.

Lastly, willingness to share personal data aims to measure individuals' readiness to share personal data with (1) friends, (2) health professionals, (3) health researchers and (4) insurance companies. Research found a negative association of privacy concerns on willingness to share personal health data (Zhu et al., 2020). Moreover, Fox and Connolly (2018) researched mobile health technology adoption across various generations and found that the unwillingness to adopt mHealth arises from mistrust, high-risk perceptions, and a strong desire for privacy. Belanger and Crossler (2011) but also Smith et al. (2011) supported these findings and reported that individuals' privacy concerns influence the willingness to disclose information and thus also the adoption intention of mHealth technologies. Therefore, it can be possible that the concept willingness to share personal information have an impact on the adoption intention of smartwatches.

Based on previous research it becomes clear that despite all advantages of smartwatches, individuals are still concerned about the risks. Therefore, it is important to explore whether these factors essentially contribute to individuals' adoption intention of smartwatches. However, besides the mentioned risk factors the interpersonal differences should be also considered, since personality plays a major role in individuals' behavior and decision making (Digman, 1990).

The Role of Personality

Personality can be described as a combination of patterns that influence behavior, thought, motivation, and emotion in a human being (Digman, 1990). Personality not only influences how individuals move and respond in their environment, but it also causes people to act in certain ways (Digman, 1990). Therefore, it is important to also have a look at personality when it comes to the adoption intention of smartwatches since personality plays a major role in individuals' behavior. Several models were developed to measure individuals' personality, however, the most popular and widely used model to identify was developed by Goldberg (1993) and named the Big Five Inventory (BFI). The Big Five personality traits are (1) agreeableness, (2) emotional instability (also called neuroticism) (3) extraversion, (4) openness to new experience, and (5) conscientiousness, (Goldberg, 1993). The personality trait *agreeableness* is characterized as being social conform, warm, kind, cooperative, trusting, and flexible. Agreeableness is seen as a measure of how friendly people are, with high ratings being associated with individuals who are kind, sympathetic and warm (McCrae & Costa, 1991). Research shows that individuals scoring low on agreeableness have greater privacy concerns which in turn might negatively influence the adoption intention of smartwatches (Digman, 1990).Whereas agreeable individuals were found to be more trusting towards technology (Digman, 1990). Moreover, Devaraj et al. (2008) found agreeable individuals to have high perceived usefulness beliefs about technology. This means that agreeable individuals are especially likely to believe that technology would enhance their performance. Therefore, it should be investigated whether agreeable individuals are more likely to adapt smartwatches than disagreeable individuals.

Emotional instability is defined as a measure of affect and emotional control, with low levels meaning emotional stability and thus a good overall control over emotions whereas high levels describe stressed and worried individuals with an overall emotional instability (McCrae & Costa, 1991). Early opinions suggest that emotionally unstable people show greater levels of computer anxiety (Korzaan, & Boswell, 2008) and are likely to avoid internet use (Tuten, & Bosnjak, 2001). However, further research has failed to support this hypothesis and it is nowadays considered that emotionally unstable individuals use the internet frequently, mostly to avoid loneliness (Amichai-Hamburger, & Ben-Artzi, 2003; Butt, & Phillips, 2008). Emotionally unstable people are generally more nervous and worried and display both anxiety and ager, which might result in negative attitudes toward adopting smartwatches (McCrae & Costa, 1991).

Individuals high on *extraversion* seek interaction with the environment and feel very comfortable and assertive in social situations. Whereas introverted individuals are typically shy and quiet (McCrae & Costa, 1991). Research has established a positive association between the personality trait extraversion and the gender female on the use of the internet (Amichai-Hamburger, & Ben-Artzi, 2003). Especially in the personal fitness context, extraverts were found to be more likely to technologies with social features, due to the possibility to share their achievements (Manner, & Lane, 2012). Similarly, Roger and Jamieson (1988) suggest that the desire to gain social status is one of the most important motivations to adopt new innovations. Therefore, it can be stated that extraverts might have more positive attitudes to adopt mHealth technology.

Open to new experience can be described as those individuals, who enjoy trying new things, are curious and unconventional. They prefer variety and value independence. Openness to new experience has been shown to be related to a higher degree of information seeking (McElroy et al., 2007). Besides that, individuals having this trait have a strong motivation to learn, therefore individuals might consider using technology to learn more about their health and physical fitness (Major et al., 2006). From this Major et al. (2006) concluded that people who are more open to new experiences appear more motivated to accept novel technologies. Moreover, Nunes et al. (2018) researched the effects of personality on individuals' intentions to use mHealth technologies and found that openness to new experience positively correlates with the intention to use mHealth technologies. Based on all mentioned information openness to new experience might have a positive influence on using and adoption smartwatches.

Conscientious individuals can be described as organized, dependable, thorough, and exacting. In terms of smartwatch adoption conscientious individuals are likely to consider ways in which technology can be used to enhance their effectiveness and perform better in life (Barrick, & Mount, 1991). Similar to openness to new experience, conscientious individuals have a strong desire to learn and acquire new information (Major et al., 2006). Therefore, it can be concluded that conscientious individuals will be likely to use smartwatches. However, research also found that conscientious individuals are likely to be concerned about other action (Junglas et al., 2008). This implies that they would be concerned about what others will do with their private information and thus be concerned about their privacy (Junglas et al., 2008). Therefore, future research is required to detect the direction of the relationship between conscientiousness and adoption intention of smartwatches.

The research in this field is still in its infancy and no other study assessed individuals risk perception and personality in relation to smartwatch adoption intention for physical fitness. Therefore, due to the research gap in this field, the first aim of this study is to explore the following research question: *Which risk perception factors (privacy risk, performance risk, legal concern, and trust) are associated with the adaption intention of smartwatches for personal fitness in young adults*? The second aim of this study is to explore the research question: *Which personality types are associated with the adaption intention of smartwatches for personal fitness in young adults?*

Methods

Design

A cross-sectional online survey design was used to explore (1) which risk perception factors and (2) which personality types are associated with the adoption intention of smartwatches. This was accomplished by convenience and snowball sampling of 104 participants. The independent variables were the risk perception concepts *privacy risk*, *performance risk*, *legal concern*, *trust and willingness to share personal information* and the personality types: *agreeableness*, *emotional instability*, *extraversion*, *openness to new experience, and conscientiousness*. The dependent variable was adoption intention to use smartwatches for personal fitness.

Participants and Recruitment

The participation of 104 subjects in the online survey was voluntary with the inclusion criteria: (1) to be aged from 18 to maximum of 35 years and (2) have sufficient German skills since the survey was translated to the German language. Data from participants who did not fulfil the requirements were not included in the analysis. Based on the convenience sampling method participants were recruited. Snowball sampling method was used, and the study was spread in the researcher's private network. Before the participants filled out the survey a digital informed consent had to be signed in (Appendix A). During the period from 7th December to 14th December, data was collected.

The final sample for this study was made of 101 participants. Due to incomplete answers on the Risk Perception and Adoption Intention of Smartwatches questionnaire three participants were excluded. Overall, the participants had mostly German nationality (89%) with the mean (*SD*) age of 25 (5.1) years. The gender was distributed approximately equal (51% males). Most of the respondents reported not to use smartwatches (60 %) (see Table 1).

Table 1.

Characteristics of the Sample (N = 101) with Mean (M) and Standard Deviation (SD) for Age.

	Characteristics	**Frequency**	
Age, M (SD)			25.9 (5.1)
Gender (%)	Male	51	(51%)
	Female	50	(50%)
Nationality (%)	German	90	(89%)
	Other	11	(11%)
Educational level (%)	Primary school	8	(8 %)
	Secondary school	34	(34%)
	Post-secondary vocational education	20	(20 %)
	Bachelor	28	(28 %)
	Master	8	(8 %)
	PHD	3	(3 %)
Smartwatch use (%)	No	60	(60 %)
	Yes	41	(41 %)

Materials

To explore the association of the risk perception factors and personality with adoption intention the following questionnaires were used.

Risk Perception and Adoption Intention of Smartwatches questionnaire

The Risk Perception and Adoption Intention of Smartwatches questionnaire (Appendix B) was developed to measure individuals risk perception and the intention to adopt smartwatches. The items for the scale's *privacy risk* (α = .91*), performance risk (* α = .85), *legal concern (*α = .84), *trust* (α = .87), and *adoption intention* (α = .85) were derived from Deng et al. (2018), whereas items for the scale willingness to share personal data were developed independently. All items were slightly modified to fit the research context and translated to the German language. Moreover, all questions were measured with a five-point Likert Scale ranging from 1 'Strongly disagree' to 5 'Strongly agree'. The mean total scores for each scale were calculated, with a maximum score of five and a minimum score of one.

Privacy Risk

The scale privacy risk measured individual privacy concerns when using smartwatches and consisted of four questions (Deng et al., 2018). The (1) first question assessed individuals' concerns about the storage of their personal data, the (2) second question assessed the concerns that smartwatch companies might use the personal data for other purposes, the (3) third item measured the concerns about the misuse of personal data by cybercriminals and the last (4) item measured concerns about personal information leakage e.g.: *"Because of security issues I am worried about personal fitness information leakage when using the smartwatch" (*Appendix B).

Based on the Cronbach's alpha analysis the reliability of the scale privacy risk was unacceptable (α = .39). To increase the reliability the second item was deleted (α = .45). The Cronbach's alpha analysis indicated that deleting more items would not rise the reliability coefficient. Since the reliability of this scale was still unacceptable it was decided to use single items of this scale in further analysis.

Performance Risk

Next, the scale performance risk was made of four items. The (1) first item covered individuals' concerns that smartwatches cannot satisfy the health and fitness needs. The (2) second item measured individuals' concerns about the credibility of data. Further, the (3) third item explored individuals' worries that the health and fitness information measured by the smartwatch will not match individuals' expectations. Lastly, the (4) fourth item compared the quality of traditional offline sport inspection services with the quality of smartwatches measures e.g.: *"Compared to traditional offline sports inspection services, I am concerned about the quality of my health status reported by smartwatches or wearables* ".

The scale performance risk scored an unacceptable Cronbach's alpha of α = .27. The Cronbach's alpha analysis indicated to delete the fourth item of the scale to increase the reliability. By deleting the fourth item the scale resulted in a Cronbach's alpha of α = .39 which was still not acceptable. Moreover, the analysis indicated that deleting more items would not rise the reliability coefficient. Therefore, it was decided to use single items of this scale in further analysis.

Legal Concern

The scale legal concern measured individuals concerns about the protection of their rights by law when using smartwatches with three items. The first (1) item measured individuals concern about the protection of the rights by law when using smartwatches. The second (2) question measured whether individuals are concerned about the lack of law enforcement in the smartwatch context. Lastly, the third (3) item measured the concerns that using apps which are connected with the smartwatch, the personal information is not protected by law*:" I am worried that my personal fitness information is not protected by law when using online apps connected with smartwatches or wearables"*.

Overall, the reliability of the scale legal concern was unacceptable α = .24. The Cronbach's alpha analysis indicated that by deleting the third item the reliability of this scale will rise to α = .66. Therefore, the third item was deleted, and the final scale was made of two items (α = .66).

Trust

Next, the scale trust measured individuals trust in fitness recommendations given by smartwatches with four questions. The first (1) item measured the trustworthiness of the advices given by smartwatches.

Further, the second (2) item measured the extent to which individuals believe that health and fitness advises are developed by health experts. The third (3) item measured individuals' overall trust in the advices of the smartwatch. Lastly, the fourth (4) item covered the objectivity and credibility of the health and training advises e.g.,*" I think the personal health advices provided by smartwatches and wearables are verified by objective criteria and the credibility is guaranteed"*.

Overall, the scale trust had an unacceptable Cronbach's alpha of α = .42. The third (α =.56) and fourth (α = .71) items were removed to increase the reliability of the scale. The final scale was made of two items with a reliability coefficient of α = .71.

Willingness to Share Personal Data

Willingness to share personal data measured individuals' readiness to share the collected information like daily steps, stress level, sleep quality, distance, pace, GPS track or burned calories with friends, health professionals, health researchers and insurance companies. Overall, the scale was made of four questions. The first (1) question measured the willingness to share personal information with friends, the second (2) with health professionals, the third (3) with health researchers and fourth (4) with insurance companies for smaller rewards like lower costs or more personalized service. Each of the four questions measured the willingness to share: the number of steps, running/walking speed, calories burned, route/GPS information, heart rate, blood oxygen level, respiration rate, stress level, and lastly the skin temperature. For each of these questions' participants could answer on a five-point Likert scale ranging from 1 'Strongly disagree' to 5 'Strongly agree'. The scale willingness to share personal data showed a good Cronbach's alpha (α = .96).

Adoption intention

Lastly the scale adoption intention measured individuals' intention to adopt smartwatches for physical fitness with four items. The first item (1) measured the willingness to use a smartwatch to counteract health problems, the second item (2) measured the willingness to use a smartwatch to monitor the health and fitness status, the third item (3) measured the willingness to use smartwatches and lastly, the fourth item (4) measure the intention to buy a smartwatch to monitor the personal health and fitness situation. One example item is: *"I am willing to use a smartwatch or wearable to monitor my health and fitness status".*

The scale adoption intention had an unacceptable Cronbach's alpha of α = .32, where to increase the reliability of the scale the fourth (α = .47) and third (α = .73) items were eliminated. The final scale was made of two items with a reliability coefficient of α = .73.

The Big Five Inventory – 2 Short Form

The second questionnaire that was used in this study is the Big Five Inventory–2 Short Form (BFI-2-S) which measured individuals' personality (Soto, & John, 2017). The questionnaire consisted of 30 different questions where all items were answered on a five-point Likert Scale ranging from 1 meaning 'Strongly disagree' to 5 meaning 'Strongly agree'. The questionnaire covered five personality types namely: extraversion (α = .86), agreeableness (α =.82), conscientiousness (α =.88), emotional instability (neuroticism) (α =.90) and openness to new experience (α =.84) (Soto, & John, 2017). The full questionnaire is attached in Appendix C.

The results were scored with a scoring key from Soto and John (2017) where three items for each personality type were scored reversedly. For the personality type extraversion items 1, 21, 26, agreeableness items 7, 17, 27, conscientiousness items 3, 8, 28, negative emotionality items 14, 19, 24 and lastly openness to new experience items 10, 20 and 30 were scored reversedly. The mean total scores of the scales were calculated with the highest score of five and the lowest score of one.

Procedure

The study took overall, 7 days. Participants received a brief description of the study through the Qualtrics website. Thereafter, respondents had to sign a digital informed consent (see Appendix A), which encompasses the right to withdraw at any given time for any reason. Moreover, the informed consent provides the respondents with the information that the collected data was anonymized where the name and all trackable information to the person were deleted. All data was transmitted to a secure storage system and was stored in files and folders on the researcher's laptop. After signing the informed consent, participants could proceed and fill out first the BIF-2-S questionnaire and afterwards the Risk Perception and Adoption Intention of Smartwatches questionnaire where each takes approximately ten minutes. After participants filled out both questionnaires they were thanked for the participation and were informed about the possibility to contact the researcher if they had any questions or were interested in the outcomes of the study.

Data Analysis

The data analysis was conducted with the software IBM SPSS Statistics (Version 25). First, all data was transmitted from the survey platform Qualtrics to the IBM SPSS statistics software. Secondly, the dataset was cleaned where all missing values were deleted listwise, meaning deleting cases already with one missing value. Thus, the analysis was only run-on cases which have a complete set of data and a response rate of 100%.

Afterwards, descriptive statistics were calculated for sociodemographic variables like age, nationality, and gender to examine the distribution of the sample characteristics. To assess the distribution of the risk perception concepts, descriptive statistics of the Risk Perception and Adoption Intention of Smartwatches questionnaire were calculated. Similarly, to investigate the scores on the Big Five Inventory - 2 Sort Form descriptive statistics of the BIF-2S questionnaire were computed.

To explore the research question: *Which risk perception factors (privacy risk, legal concern, trust and willingness to share personal data)* and *which personality types (agreeableness, emotional instability, extraversion, openness to new experience, and conscientiousness) are associated with the adaption intention of smartwatches for personal fitness in young adults?"* a multiple linear regression analysis was accomplished. However, to select which variables to include in the multiple linear regression analysis fist, the univariate analysis was performed.

Univariate Analysis

Due to the low reliability of the scale's privacy risk and performance risk, it was decided to use single items. Therefore, the Pearson's correlation analysis was performed to select which single items will be used in further analysis. Next, the Pearson's correlation analysis was performed for all other independent variables with adoption to select which variables to include in the multiple linear regression analysis. All p-values below .05 indicate significant correlation with adoption intention and were included in multiple linear regression analysis (Schober et al., 2018).

Multiple Linear Regression Analysis

Before performing multiple linear regression analysis four assumptions should be tested: (1) normality, (2) linearity, (3) multicollinearity and (4) homoscedasticity of data (Osborne & Waters, 2002). The first assumption normal distribution (1) of the independent variables and the dependent variable - adoption intention was tested with the Shapiro-Wilk test. All p-values above .05 indicated a normal distribution of the data (Razali, & Wah, 2011). Next, linearity (2) of the of the independent variables (privacy risk, performance risk, legal concern, trust, willingness to share) was tested by plotting standardized residuals against standardized predicted variable. If the scatterplot shows a random pattern when the variables have a linear relationship with the dependent variable (Garson, 2012). To test for multicollinearity (3) of the independent variables the variance inflation factor (VIF) values were assessed. VIF values of 1 indicate no multicollinearity, whereas values exceeding 10 indicate high multicollinearity (Tranmer et al., 2020). Lastly, the homoscedasticity (4) assumption was tested. This was done by plotting the standardized residuals against the standardized dependent variable. This assumption was met if the scatterplot shows a random pattern of the residuals across the whole range of the dependent variable adoption intention (Nimon, 2012). Finally, multiple linear regression analysis was run including all variables which were significantly correlated with the dependent variable adoption intention and fulfilled the assumptions.

Results

Overall, the participants reported most frequent that their smartwatches can measure the number of steps (93 %), calories burned (93%), heart rate (85%) and running or walking speed (58%). Interestingly, individuals reported monitoring the heart rate (85%) most frequently, followed by the stress level (17%). Among the apps *Garmin Connect, Strava, Runkeeper, Google fit, Runtastic, Zombies, Run!, Endomondo and Nike + Run Club* individuals reported that their smartwatch is connected only to Google Fit (32%), Runtastic (22%) and Nike + Run club (20%) (Table 2).

Table 2

Smartwatch Features Reported by the Users ($N = 41$) [a]

Question item	**Answer possibilites**	**Frequencies**	**%**
What does your smartwatch measure?	Number of steps	38	93%
	Calories burned	38	93 %
	Heart rate	35	85%
	Running/ walking Speed	24	58%
	Stress level	13	32%
	Route	12	29%
	Respiration Rate	12	29%
	Blood oxygen level	4	10%
			5%
	Skin temperature	2	
What do you monitor on your smartwatch?	Heart rate	26	63%
	Stress level	7	17%
	Respiration rate	3	7%

	Route	1	2%
Which apps are connected to your smartwatch?	Google fit	13	32%
	Runtastic	9	22%
	Nike+ Run club	8	20%

[a] multiple response options were possible

Univariate Analysis

Due to the low reliability of the scale's privacy risk and performance risk correlational analysis was performed to identify which single items can be used in regression analysis. Pearson's correlation analysis of the single items of the scale privacy risk with adoption intention indicates that only the first item: ": *I am afraid that Smartwatch companies store and monitor my personal fitness information"* significantly negative correlates with adoption intention (r = - .27). Whereas item two (r = - .13) item three (r = - .16) and item four (r = - .15) do not show significant correlations. Therefore, only the first item of the scale privacy risk was used in further analysis. Next, single items of the scale performance risk were correlated with adoption intention. Correlational analysis indicated that the first item (r = - .07) the second item (r = - .10) the third item (r = - .13) and the fourth item (r = - .09) were not significantly correlated with adoption intention and thus the scale was not used in further analysis.

Further, only the scales trust (r = .32), willingness to share with health professionals (r =.22) and extraversion (r = -.27) significantly correlates with adoption intention. Whereas all other scales do no show significant correlation with adoption intention: legal concern (r = -.5), willingness to share with friends (r =.09), willingness to share with health researchers (r = -.04), willingness to share with insurance companies (r = .08), agreeableness (r =.13), conscientiousness (r =.1), negative emotionality (r =.09) and openness to new experience (r = -.03). Therefore, based on the analysis the first single item of the scale privacy risk and the variables trust, willingness to share with health professionals and extraversion were included in the regression analysis.

Risk Perception and Adoption Intention of Smartwatches

Results on the Risk Perception and Adoption Intention of Smartwatches questionnaire indicate a high adoption intention of smartwatches mean (*SD*) 4.32 (.7). This means that participants are likely to adopt smartwatches to monitor their health and fitness status. Interestingly, most of the participants reported to have neither privacy 2.32 (1.1) nor legal concerns 2.27 (.5) by using smartwatches. Which means that individuals do not worry about the abuse of their data in terms of privacy and are also not concerned about the lack of law enforcement in the smartwatch context. However, individuals trust in smartwatches was low 2.63 (0.6). Moreover, it was found that among the willingness to share personal data, the willingness to share data with health professionals was scored the lowest 2.62, (1.1) whereas the willingness to share data with health researchers was scored the highest 2.88, (1.2) which implies that individuals are more likely to share sensitive information with health researchers compared to health professionals (Table 3).

Personality

The descriptive statistics of the BIF-2-S questionnaire are displayed in table 4. The results indicated that most respondents scored above the average for the trait extraversion (3.48) since the reference group indicated lower scores. This implies that the sample is more extraverted compared to the average of German individuals aged from 21 to 35 years (Soto & John, 2017). Interestingly solely the trait emotional instability (3.30) was scored averagely in comparison to the reference group. Besides that, individuals scored below the average for the trait's agreeableness (3.16), conscientiousness (3.19) and openness to new experience (3.36). This suggest that individuals in this sample are less agreeable, conscientious, and open to new experience than the average of German individuals.

Table 3.

Mean and Standard Deviations (SD) of the Risk Perception and Adoption Intention of Smartwatches Questionnaire N = 101 (score range from 1' Strongly disagree' to 5 'Strongly agree').

Domain	**Items**	**Mean**	**SD**
Adoption intention	2	4.32	0.7
Willingness to share with health researchers	7	2.88	1.2
Willingness to share with insurance companies	7	2.72	1.1
Willingness to share with friends	7	2.67	0.5
Trust	2	2.63	0.6
Willingness to share with health professionals	7	2.62	1.1
Privacy risk	1	2.32	1.1
Legal concern	2	2.27	0.5

Table 4.

Mean, Standard deviation (SD), of the Total Sample (N = 101) for the BIF-2S Questionnaire (score range from 1' Strongly disagree' to 5 'Strongly agree') Compared to the Mean Scores of a Similar Reference Group

Personality type	**Mean (SD)**	**Mean Norm Group**
Extraversion	3.48 (.5)	3.25 - 3.29[a]
Openness to new experience	3.36 (.5)	3.92 - 3.90[a]
Emotional instability	3.30 (.6)	3.32 - 3.19[a]
Conscientiousness	3.19 (.6)	3.45 - 3.68[a]
Agreeableness	3.16 (.6)	3.64 - 3.75[a]

[a] Soto & John, 2017

To answer the questions (1) which risk perception factors and (2) which personality types are associated with the adoption intention of smartwatches for personal fitness, first univariate analysis and second multiple linear regression analysis was performed based on data from 101 participants.

Assumptions of Multiple Linear Regression Analysis

To assess the normality of the data the Shapiro-wilk test was performed. It was found that the variables*:* privacy risk W (24) = .92, p = .07, trust W (15) = .93, p = .24, willingness to share with health professionals W (7) = .82, p = .06 and extraversion W (12) = .92, p = .27 were distributed approximately normal. Next the linear relationship between the independent variables: privacy risk, trust, willingness to share with health professionals and extraversion with adoption intention was assessed. The scatterplot shows a random pattern which means that the independent variables have a linear relationship with adoption intention and thus, suggests this assumption to be fulfilled. Further multicollinearity of the independent variables was assessed by computing the VIF values. Based on the analysis, no multicollinearity between the independent variables was found since all VIF values were under 10, ranging from 1.0 to 2.1. Finally, the homoscedasticity of data was assessed by plotting the standardized residuals against the standardized dependent variable. The scatterplot shows no patterns in the distribution of the residuals which means that this assumption is met.

Multiple Linear Regression Analysis

Finally, the multiple regression analysis was run, including the independent variables: *privacy risk, trust, willingness to share personal data with health professionals, extraversion* and the dependent variable adoption intention. The regression model indicates that collectively the variables predict individuals' adoption intention significantly, whereas independently only privacy risk (p = .04) and trust (p = .005) are statistically significant predicting adoption intention. The variables willingness to share personal data with health professionals (p = .22) and extraversion (p = .06) were found to be not significant. Therefore, it was decided to reduce the model by eliminating one variable at a time based on the highest p-value. The variable willingness to share personal data with health professionals was eliminated from the model and extraversion turned to be statistically significant (*p* = .036). The final regression model (Table 5) included the variable's extraversion (*p* = .036), trust (*p* =.003) and privacy risk (*p* =.025) and show to predict 20% of the variance in adoption intention R^2 = .20, *F* (3, 46) = 7.95, *p* = .000. The variable trust shows to have a positive relationship with adoption intention, whereas the variables privacy risk and extraversion shows to have a negative relationship with adoption intention. This implies that individuals trusting smartwatches are also more likely to adopt that technology, whereas individuals who have privacy concerns or are extraverted personalities are not likely to adopt smartwatches.

Table 5.

Regression Model of Trust, Privacy Risk and Extraversion with Adoption Intention

Variable	**B**	**SE B**	**ß**	**t**	**p**
Trust	.25	.083	.27	3	.003
Privacy Risk	-.51	.22	.21	2.27	.025
Extraversion	-.22	.10	-.19	-2.12	.036

R^2 =.20, *F* (3, 46) = 7.95, *p* =.000

Discussion

The aim of this study was to explore whether the concepts of risk perception *(privacy risk, legal concern, trust)* and the Big Five personality types (*agreeableness, emotional instability, extraversion, openness to new experience, conscientiousness*) are associated with the adoption intention of smartwatches for the personal fitness in young adults. The results indicate that only trust is positively associated with adoption intention whereas extraversion and privacy risk are negatively associated with adoption intention.

The results show that trust has a positive association with the adoption intention of smartwatches for personal fitness. Likewise, numerous health studies found strong positive effects of consumers' trust on their satisfaction and continuance intentions (Deng et al., 2018; Li et al., 2016). For instance, Li et al. (2016) examined individuals' adoption of healthcare wearable devices and found trust to be significant for continuously using wearable devices. Similarly, Deng et al. (2018) researched the predictors of patient's adoption intention of mHealth services and found that individuals trust in mHealth services positively affects their adoption intention. Based on that, Deng et al. (2018) concluded that individuals trust in mHealth technologies helps to decrease individuals concerns about that technology which in turn has a positive effect on the adoption intention. Tu (2018) research adoption intention of Internet of Things (objects which are embedded with sensors, software, and other technologies to connect and exchange data with other devices over the internet) (Ashton, 2009) and supported these findings. It was found that the reduction of the uncertainty factors (risks, fears) increases the trustworthiness of Internet of Things technology and consequently enhanced the intention to adopt IoT technology (Tu, 2018). However, in the context of smartwatches, no research assessed the influences of trust on adoption intention for personal fitness, therefore no conclusions about the influences of trust on adoption intention of smartwatches for personal fitness can be made. Based on previous research is only clear that trust seems to have some influences on adoption intention, which require future research to investigate the influences for smartwatch adoption in the context of personal fitness.

While trust was found to be positively associated with adoption intention, the personality type extraversion has a negative association with smartwatch adoption. This means that extraverted individuals are not likely to adapt smartwatches for personal fitness, which is not in line with previous research. Choi and Kim (2016) researched the association of interpersonal differences with adoption intention of smartwatches and found that extraverts are more likely to use smartwatches compared to introverts, however more as a fashion accessory rather than as a technology. Therefore, Choi and Kim (2016) concluded that individuals with a higher need for uniqueness and self-presentation tend to wear smartwatches to express themselves and enhance their social status. In fact, extraverts are characterized as individuals with a higher need for socialization, self-presentation, and uniqueness (McCrae & Costa, 1991). Based on these findings it becomes clear, that extraverted individuals tend to use smartwatches as a way of social assimilation and self-presentation to their environment. Already Katz and Blumler (1974) indicated that different people might use the same media for different purposes. While open individuals would use media for inspiration or as a source to receive new information, extraverted individuals would use the same media to socialize with peers (Katz, & Blumler, 1974). Conclusive it can be stated that extraverts are likely to use smartwatches as a fashion accessory which promotes self-presentation.

Lastly, privacy risk was found to have a negative influence on individuals' adoption intention of smartwatches. This means individuals having concerns about their privacy are not likely to adapt smartwatches for personal fitness. Similar findings were found in the study of Gao and Bai (2014) which researched factors that influence the acceptance of the Internet of Things (IoT). The findings in this study suggest that privacy concerns have a negative relationship with adoption intention of IoT (Gao, & Bai, 2014). These results can be explained with the privacy calculus theory. The privacy calculus theory aims to explain individuals' decision-making process and emphasize that before taking a decision, individuals will rationally weigh the potential risks and benefits of that decision (Dinev, & Hart, 2006). Since smartwatches have not only distinctive advantages to enhance personal fitness and improve health, smartwatches have also high levels of privacy risk. This might cause individuals to face the tradeoff between perceived benefit and perceived risk of smartwatch adoption (Dinev, & Hart, 2006). For people with a high-risk perception and low perceived benefits of smartwatches, their privacy calculus would overweight the risks and consequently taking the decision not to adapt smartwatches. However, for individuals with a low-risk perception and high perceived benefits of smartwatches, the decision will rather be to adapt smartwatches. However future research is required to include a reliable scale measuring privacy concerns since the scale utilized in this research was made of only one item to measure privacy risk, which is not an accurate measure.

Strengths and Limitations

The present study has several strengths. The first strength is that this study focuses on the age group of young adults rather than looking more broadly at different age groups. Research shows that the most decline in physical activity happens from the transition of adolescence to adulthood. Therefore, to increase individuals' activity it is important to focus on the age group where active behavior starts to develop into sedentary behavior. Since this study focuses on young adults, new insights were found which can be used in further research. This can facilitate the development of interventions that are effective in promoting physical activity, especially for this age group. Another strength of this study is that it aids the research of smartwatches adoption since no research was done incorporating (1) the risk perception factors, (2) personality and (3) the age group of young adults to assess the adoption intention of smartwatches in the personal fitness context. With this study, not only the need for development in this research field was indicated but also the first steps were made towards widening the knowledge in this area.

While the strengths have been already assessed, the study has also some limitations. The first limitation is the low reliability of the Risk Perception and Adoption Intention of Smartwatches questionnaire. The low internal consistency of the items suggests that those items were not measuring the same construct. Due to the low internal consistency, items were removed to increase the reliability where some scales were made solely of one (*privacy risk*), or two items (*adoption intention*, *legal concerns*, *trust*). This is, however, not an accurate measurement of the risk perception and adoption intention of smartwatches and could lead to distorted results. Performing first a pretest of the questionnaire, before starting with data collection would be a possibility to prevent having a low internal consistency. Another limitation is that this study does not differentiate between participants who want to improve their physical activity and participants who do not want to improve. This however can distort the results for the adoption intention of smartwatches. If for instance, the majority of the respondents are not interested in improving their activity, they would not be likely to use smartwatches for physical fitness. Therefore, including questions to measure individuals' intentions of being active or wanting to increase their activity would increase the accuracy of the measurement.

Future Research and Conclusion

Based on the limitations three recommendations for future research can be given. First future research should investigate the adoption intention of smartwatches for physical fitness since this area is still in its infancy. Concretely, it is recommended (1) to do a second survey study to assess individuals risk perception and adoption intention of smartwatches. Since this study uses a questionnaire that was found to be not an accurate measure of individuals risk perception and adoption intentions another study should replicate the design however with a reliable survey. By replicating the study and having similar findings as in this study the validity of the findings increases. But having different findings would also add new knowledge to the general field of mHealth technology adoption for physical activity. Besides this, (2) the questionnaire should include questions measuring individuals' intentions to improve their physical activity since this can significantly affect the results. If participants do not have the aim to improve their physical level the results for adoption intention of smartwatches for personal fitness would be distorted. Lastly, (3) variables should be included in the questionnaire relevant to the adoption intention of the specific age group of young adults. Since the results on the Risk Perception and Adoption Intention of Smartwatches questionnaire indicated that young adults are not concerned about the possible risks of smartwatches and moreover, the explained variance of adoption intention by risk perception was not high it might be the case that other variables would affect the adoption intention of smartwatches to a greater degree.

Overall, this research aims to explore which risk factors and which personality types are associated with the adoption intention of smartwatches for physical fitness. This study concludes that the risk factors privacy risk, trust and the personality type extraversion are associated with the adoption intention of smartwatches. These concepts explain 20% of the variance in adoption intention which is not high but still indicates that these concepts are relevant and should be assessed in further research. Moreover, these findings can be considered by designers of technological interventions. For instance, designers of mHealth technologies could consider to decrease individual’s privacy concerns and with that increase individual’s trust. As privacy risk is found to have a negative association with adoption intention and trust has a positive association, it could increase individuals’ adoption intention of smartwatches. As one of the major privacy risks of individuals is the unclear distribution of their data and its use by third parties, smartwatch designers could lower individuals concerns and increase their trust by clearly communicating how the personal data will be used. If the risks of smartwatches would be reduced individual’s privacy calculus would overweight the benefits rather than the risks of using smartwatches which would increase individual’s adoption intention. However, based on the results it is also important to consider individual personality in the design of interventions. As research suggests that extraverted individuals are likely to use smartwatches for self-presentation and socialization with their environment, social features of smartwatches could be improved thus making it more suitable to be used by extraverts. Since previous research suggests that personality influences the adoption of mHealth technologies, and this research indicates personality to have an association on adoption intention, integrating personality differences in the design can be an effective solution to increase individuals’ adoption intention. Even if this study does not have a high explanatory power, it provides researchers and mHealth technology designers with insightful information for the development of further interventions.

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Appendices

Appendix A.

Informed Consent

In this research will be explored which risk perception factors and personality types were associated with the intention to adopt smartwatches for the personal fitness in young adults. You will be asked questions (1) about your risk perception of smartwatches (privacy risk, legal concern, trust and willingness to share personal data) and your adoption intention of mHealth technology for personal fitness. This will take you approximately five minutes. Besides that (2) questions will be asked measuring your personality which covers five main personality traits: *agreeableness, emotional instability, extraversion, openness to new experience, and conscientiousness*. For this part of the survey, you will also need approximately 5 minutes. Your data will be treated confidentially and anonymously. Your participation is voluntary, you have the right to withdraw from the online survey without reasoning yourself. In case if you will have questions or you are interested in the study outcome you can contact Alexandra Sokolova under the following e-mail address: o.sokolova@student.utwente.nl

I declare that I have considered and read the provided information about the research.

o Yes, I agree o No, I do not agree.

Appendix B.

Questions Included in the Risk Perception and Adoption Intention of Smartwatches questionnaire

1. What is your age?

   18 – 35

2. What is your educational level?

[ ] Primary School

[ ] Secondary School/MBO

[ ] Post-secondary vocational education

[ ] Bachelor

[ ] Academic Master

[ ] PhD

3. What best describes your gender?

[ ]Male

[ ]Female

[ ]Other

4. What is your nationality?

[ ]German

[ ]Dutch

[ ]Other

5. Do you have a wearable or a smartwatch?

[ ]Yes

[ ]No

6. What activities are measured with your wearable or smartwatch? (you can select multiple options)

Physical activity

[ ] Number of steps

[ ] Running/ walking Speed:

[ ] Calories burned

[ ] Route (GPS information)

Cardiovascular activity:

[ ] Heart rate

[ ] Blood oxygen level

[ ] Respiration rate

[ ] Stress level

[ ] Skin temperature

7. What activities are you monitoring with your device? (you can select multiple options)

Physical activity

[ ] Number of steps

[ ] Running/ walking Speed

[ ] Calories burned

[ ] Route (GPS information)

Cardiovascular activity:

[ ] Heart rate

[ ] Blood oxygen level

[ ] Respiration rate

[ ] Stress level

[ ] Skin temperature

8. What personal fitness apps are connected with your device? (i.e. you've allowed these apps to use the personal fitness data collected with your device) you can select multiple options

[ ] Garmin connect
[ ] Strava
[ ] Runkeeper
[ ] Google Fit
[ ] Runtastic
[ ] Zombies, Run!
[ ] Endomondo
[ ] Nike+ Run Club

Privacy risk

9. PVR1: I am afraid that Smartwatch companies store and monitor my personal fitness information.

   I strongly disagree [ ], I disagree [ ], Neither agree nor disagree [ ], I agree [ ], I strongly agree [ ]

10. PVR2: I am worried that my personal fitness information will be used for other purpose if I use the smartwatch.

    I strongly disagree[ ], I disagree [ ], Neither agree nor disagree [ ], I agree [ ], I strongly agree [ ]

11. PVR3: I am worried that when using smartwatches, my personal fitness information will be abused by cybercriminals.

    I strongly disagree[ ], I disagree [ ], Neither agree nor disagree [ ], I agree [ ], I strongly agree [ ]

12. PVR4: Because of security issue, I am worried about personal fitness information leakage when using the smartwatch.

    I strongly disagree[ ], I disagree [ ], Neither agree nor disagree [ ], I agree [ ], I strongly agree [ ]

Performance risk

13. PER1: I am worried that using smartwatches or wearables will not satisfy my health and fitness monitoring needs.

    I strongly disagree[ ], I disagree [ ], Neither agree nor disagree [ ], I agree [ ], I strongly agree []

14. PER2: I am afraid that health and fitness information that is measured by smartwatches or wearables adequately address my true health and fitness status.

    I strongly disagree[ ], I disagree [ ], Neither agree nor disagree [ ], I agree [ ], I strongly agree []

15. PER4: I am worried that the health and fitness information provided by smartwatches or wearables may not match my expectations.

    I strongly disagree[ ], I disagree [ ], Neither agree nor disagree [ ], I agree [ ], I strongly agree []

16. PER3: Compared with traditional offline sports inspection services, I am concerned about the quality of my health status as reported by smartwatches or wearables.

    I strongly disagree[ ], I disagree [ ], Neither agree nor disagree [ ], I agree [ ], I strongly agree []

Legal concern

17. LEC1: I am worried that my personal health and fitness information is not protected by law when using smartwatches or wearables.

I strongly disagree[ ], I disagree [ ], Neither agree nor disagree [ ], I agree [ ], I strongly agree []

18. LEC2: I am afraid that the rights and interests of users cannot be ensured because of the lack of specific law enforcement on smartwatches and wearables.

    I strongly disagree[ ], I disagree [ ], Neither agree nor disagree [ ], I agree [ ], I strongly agree []

19. LEC 3: I am worried that my personal health and fitness information is not protected by law when using online apps connected with smartwatches or wearables.

    I strongly disagree[ ], I disagree [ ], Neither agree nor disagree [ ], I agree [ ], I strongly agree []

Trust

20. TRU1: Generally, I think health advices from smartwatches and wearables are trustworthy.

    I strongly disagree[ ], I disagree [ ], Neither agree nor disagree [ ], I agree [ ], I strongly agree []

21. TRU2: I think the health or training advises that are given by the smartwatches and wearable are developed by health experts and I have no doubt about their profession.

    I strongly disagree[ ], I disagree [ ], Neither agree nor disagree [ ], I agree [ ], I strongly agree []

22. TRU3: In general, I trust tips given by smartwatches or wearables.

    I strongly disagree[ ], I disagree [ ], Neither agree nor disagree [ ], I agree [ ], I strongly agree []

23. TRU4: I think the personal health and training advises provided by smartwatches and wearables are verified by objective criteria and the credibility is guaranteed.

    I strongly disagree[ ], I disagree [ ], Neither agree nor disagree [ ], I agree [ ], I strongly agree []

Adoption intention

24. AI1: When I face health-problems as for instance cardiac arrythmia, I guess I will use the smartwatch to monitor the heartrate.

I strongly disagree[ ], I disagree [ ], Neither agree nor disagree [ ], I agree [ ], I strongly agree []

25. AI2: Generally, I will use a smartwatch or wearable.

    I strongly disagree[ ], I disagree [ ], Neither agree nor disagree [ ], I agree [ ], I strongly agree]

26. AI3: I am willing to use a smartwatch or wearable to monitor my health and fitness status.

    I strongly disagree[ ], I disagree [ ], Neither agree nor disagree [ ], I agree [ ], I strongly agree []

27. AI4: I intend to buy a smartwatch or wearable to monitor my health and fitness status.

    I strongly disagree[ ], I disagree [ ], Neither agree nor disagree [ ], I agree [ ], I strongly agree []

Willingness to share personal fitness information.

In the following block, four questions will be asked about your willingness to share personal fitness data (daily steps, stress level, sleep quality etc.), regardless of whether you have a wearable device or not.

Please indicate your willingness by choosing one of seven statements (from strongly disagree to strongly agree).

28. I am willing to share the following personal health data with friends:

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
Number of steps	O	O	O	O	O
Running/ walking speed	O	O	O	O	O
Calories burned	O	O	O	O	O
Route / GPS information	O	O	O	O	O
Heart rate	O	O	O	O	O
Blood oxygen level	O	O	O	O	O
Respiration rate	O	O	O	O	O
Stress level	O	O	O	O	O
Skin temperature	O	O	O	O	O

29. I am willing to share the following personal health data with health professionals:

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

Number of steps	O	O	O	O	O
Running/ walking speed	O	O	O	O	O
Calories burned	O	O	O	O	O
Route / GPS information	O	O	O	O	O
Heart rate	O	O	O	O	O
Blood oxygen level	O	O	O	O	O
Respiration rate	O	O	O	O	O
Stress level	O	O	O	O	O
Skin temperature	O	O	O	O	O

30. I am willing to share the following personal health data with scientific health researchers:

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

Number of steps	O	O	O	O	O
Running/ walking speed	O	O	O	O	O
Calories burned	O	O	O	O	O
Route / GPS information	O	O	O	O	O
Heart rate	O	O	O	O	O
Blood oxygen level	O	O	O	O	O
Respiration rate	O	O	O	O	O
Stress level	O	O	O	O	O
Skin temperature	O	O	O	O	O

31. I am willing to share the following personal health data with health insurance company in exchange for benefits or rewards like lower costs or more personalized service:

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
Number of steps	O	O	O	O	O

Running/ walking speed	O	O	O	O	O
Calories burned	O	O	O	O	O
Route / GPS information	O	O	O	O	O
Heart rate	O	O	O	O	O
Blood oxygen level	O	O	O	O	O
Respiration rate	O	O	O	O	O
Stress level	O	O	O	O	O
Skin temperature	O	O	O	O	O

Appendix C.

Questions included in the Big Five Inventory (BFI-2-S)

I am someone who...

1. __ Tends to be quiet.
2. __ Is compassionate, has a soft heart.
3. __ Tends to be disorganized.
4. __ Worries a lot.
5. __ Is fascinated by art, music, or literature.
6. __ Is dominant, acts as a leader.
7. __ Is sometimes rude to others.
8. __ Has difficulty getting started on tasks.
9. __ Tends to feel depressed, blue.
10. __ Has little interest in abstract ideas.
11. __ Is full of energy.
12. __ Assumes the best about people.
13. __ Is reliable, can always be counted on.
14. __ Is emotionally stable, not easily upset.
15. __ Is original, comes up with new ideas.
16. __ Is outgoing, sociable.
17. __ Can be cold and uncaring.
18. __ Keeps things neat and tidy.
19. __ Is relaxed, handles stress well.
20. __ Has few artistic interests.
21. __ Prefers to have others take charge.
22. __ Is respectful, treats others with respect.
23. __ Is persistent, works until the task is finished.
24. __ Feels secure, comfortable with self.
25. __ Is complex, a deep thinker.
26. __ Is less active than other people.
27. __ Tends to find fault with others.
28. __ Can be somewhat careless.
29. __ Is temperamental, gets emotional easily.
30. __ Has little creativity.