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Impacts of Risks Over Benefits in the Adoption of Self-Tracking Technologies

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ABSTRACT

Self-tracking (ST) technologies offer an unlimited number of opportunities to improve human life, especially health and well-being. Many scholars have been interested in this technology because of its worldwide spread but have not emphasized the benefits versus ST practices risks. This paper presents a literature review of the benefits and risks of ST practices to close this gap. It also develops a multidisciplinary research model based on the extended valence framework. This model offers five hypotheses highlighting the importance of considering technological, social, and health factors when measuring ST adoption. The results show that the perceived benefits outweigh the risks. Health is paramount in the perception of benefits. These results lead the authors to make a few recommendations for practitioners.

KEYWORDS

Adoption, Health, Literature Review, Self-Tracking, Valence Framework

2 INTRODUCTION

The adoption of technologies in the health sector has offered new possibilities to track physiological parameters and daily activities. In particular, self-tracking technologies (STTs) that are new Internet of Things (IoT) smart technologies (Joseph et al., 2017) provide plenty of opportunities for the empowerment of patients (Nelson et al. 2016) and for the healthcare sector, especially by generating data points to be collected and analyzed. For instance, through mobile applications, STTs help manage different diseases, such as diabetes, obesity, and asthma. Having citizens adopt STTs is an essential issue for the healthcare sector regarding the reduction of medical expenses (Rich & Miah, 2017). A study conducted by Strategy Analytics indicates that smartwatch sales grew 20 percent in Q1 2020 (Waltzer, 2020). Indeed, since COVID 19, an increasing number of persons appreciates having a ST device capable of measuring their vital signs, such as oxygen levels.

While STT adoption is growing, and more academic research is being conducted on this topic (Ruckenstein & Schüll, 2017), research has not paid enough attention to the multiple facets of STT adoption. Most of the research models in information systems (IS) that deal with STT are based on the Technology Acceptance Model (TAM) (Choi & Kim, 2016; Chuah et al., 2016; K. J. Kim & Shin, 2015; Wu et al., 2011) and thus acknowledge mainly technical factors (del Río Carral et al., 2017). In their literature review, del Río Carral et al. (2017) also point out that a purely technical approach does not reflect the complexity of self-tracking (ST) practices. They identify two trends in their review:

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1) a set of enthusiastic articles that promote STT as a new hope for health management and 2) more nuanced and critical articles that discuss this practice in light of a neoliberal surveillance society (e.g. De Moya and Pallud 2020). Examining STT requires a multidisciplinary approach (De Moya & Pallud, 2017; Tuzovic, 2015) to involve health dimensions (with the promise of improved health), human and social dimensions (especially concerning privacy, human integrity, and normalization of society), and technical dimensions (regarding measurement reliability, a user-friendly interface design, and the methods used to analyze the collected data) (Lupton, 2016; Price et al., 2017). Becker et al. (2017) also suggest taking into account perceived benefits and costs that can influence the continued use of fitness trackers.

A stream of research in sociology deals with risks in society and individuals' avoidance strategies (Beck, 1992). Some risks are external, such as the risk of a nuclear accident (Beck, 1992). Others correspond to personal risks, such as smoking or eating too much fat or sugar. It is then up to the individuals to manage their own risks based on a benefit-cost calculation. To date, very few studies have focused on benefit-cost models for STT adoption. Therefore, this study is an initial attempt to bridge the existing knowledge gap in the literature. More precisely, the paper aims to address the following research questions:

- What are the perceived benefits and risks associated with STT?
- How do technological, social, and health determinants influence STT adoption?

To answer these research questions, the authors follow the works of Becker et al. (2017) and Gribel et al. (2016) on the acceptance factors of wearables. Additionally, the multidimensional perspective retained in this study is inspired by the research (Sheth et al., 1991) that takes into account different dimensions (such as functional, social, and emotional) to evaluate product value. According to Sheth et al. (1991), each of these values exerts a relative influence on the purchasing decision. Similarly, the authors would like to assess how different dimensions influence the decision to adopt STT.

The paper is structured as follows. Section 2 presents a literature review on the risks and the benefits of STTs. Section 3 introduces the extended valence framework, and the concept of risk from an IS perspective. Section 4 explains the development of the comprehensive research model. The methodology is detailed in Section 5, and the results are presented in Section 6. The final sections provide a discussion of the research outcomes, as well as suggestions for future research.

3 RISKS AND BENEFITS OF SELF-TRACKING

3.1 Definition of Self-Tracking Technologies

This research focuses on adopting and using two types of STTs, namely mobile health applications (apps) and wearables, which is presented in the following two subsections.

3.1.1 Mobile Health and Mobile Health Apps

Mobile health (mHealth), at the intersection of electronic health and smartphone technology (Adibi, 2015), enables data collection with sensors that are either integrated into the mobile technology or connected to the mobile devices via wireless or wired connections. The data are then manipulated with smartphone apps and transmitted to third parties via the cloud infrastructure. Technically, the sensors used by smartphones are the same as those in smartwatches or activity bracelets. A smartphone equipped with a tracking app can measure the physical parameters of an individual.

The mobile health tracking app is part of mHealth, defined as "medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants and other wireless devices" (WHO Global Observatory for eHealth & World Health

Organization, 2011). The mHealth tracking app generally includes wellbeing and fitness apps, which track steps and calories, lifestyle information, such as sleep, and stress management.

3.1.2 Wearables

Wearable technology refers to clothing or accessories produced or improved with electronics (Sinha & Gupta, 2019). This intelligent portable system or "smart wearable system" (Chan et al., 2012), which consists of sensors for capturing data and then storing and transmitting data on the cloud, either standalone or via a smartphone (Weber, 2015).

There are two categories of wearable materials. The first is portable technology, allowing people to use the device unobtrusively (Barth, 2013). The second category comprises intelligent textiles, integrating the technology into the fabric itself (Page, 2015). The primary purpose of these tools is to measure and/or react to environmental stimuli (Van Langenhove et al., 2012).

Fitness trackers are worn wrist bracelets that track fitness activities (steps and calories) and the users' health in real-time (Yang et al., 2016). They are also known as activity trackers, wearable fitness trackers, wearable fitness technology, smart wristbands, or smart bracelets. The primary purpose of these devices is to collect data that a user can analyze on different devices (e.g., laptop computer or smartphone). The presentation of information is very limited (e.g., pulse or time), and smart wristbands do not offer the possibility to install apps (Chuah et al., 2016).

A smartwatch is a kind of fitness tracker with extended functionalities, such as alert notifications (Gay & Leijdekkers, 2011). It is larger in size than smart wristbands and often even larger than most traditional watches. "The face of a smartwatch is usually a touchscreen. An operating and app ecosystem allows users to install various apps. It's a mini device that is worn like a traditional watch and allows for the installation and use of applications" (Yang et al., 2016, p. 277).

In addition to fitness trackers and smartwatches, the following terms were used to review the literature:

- Healthcare wearable: tracker used in a healthcare aim (diabetes, electrocardiogram, symbiotic system, etc.) (Shafi & Waheed, 2019), also known as a personal health device, wearable biomedical sensor, self-tracking technology for health fitness and wellbeing, sensor-based global health technology, wearable technology in healthcare, wearable device-based pervasive wellbeing monitoring, and smart healthcare fabric.
- General wearable: wearable technology that does not mention any detail on the device, also known as wearable ubiquitous monitoring device, body-worn sensor system, smart wearable device, and self-tracking device.

3.2 Literature Review on The Benefits and The Risks of STT

The topic of ST has been researched across various disciplines that can be grouped into three domains: technological (IS, computing science, etc.), medical, and social sciences (marketing, sociology, etc.) (De Moya & Pallud, 2017).

The researchers performed a literature search on STT adoption using several databases, namely Business Source Premier, Science Direct, Web of Science, IEEExplore, and Google Scholar. As STT is a generic term, several adjacent keywords were also used for the query, such as: "*activity tracking device*," "*fitness tracker*," "*physical activity tracking*," "*healthcare device*," "*mhealth*," "*wristband*," and "*wearable*." These keywords were used in conjunction with the terms "*adoption*," "*appropriation*," "*acceptance*," "*perception*," "*continuity*," "*commitment*," "*attitude*," and "*motivation*." The search was limited to peer-reviewed articles and excluded editorials, books, and magazine articles.

Table 1. Research publications on self-tracking tool adoption between 2008 and 2017

	Tool						
	Wearable				mHealth		
Period of publication	Fitness Tracker	Smartwatch	General wearable	Healthcare wearable	Mobile App	Multiple Types	Total
2008-2009	0	0	0	2	0	0	2
2010-2011	0	0	2	0	1	0	3
2012-2013	0	0	3	3	2	0	8
2014-2015	7	1	3	5	10	0	26
2016-2017	9	6	10	2	6	4	37

3.2.1 Findings

The search yielded 75 peer-reviewed research publications. Most research focuses on a single technology, especially fitness trackers and mobile apps. Several studies do not specify what type of wearable is being examined and simply define the technology in a general way (Table 1).

Considering the significant variables found in the 75 articles, the authors have grouped the factors affecting STT into three categories: health, social, and technological dimensions. These findings are discussed in more detail in Section 4 when developing the research model. The main factors are combined with the extended valence framework introduced in the next section.

A number of studies have applied the **theory of reasoned action** (TRA) or its extension, the **theory of planned behavior** (TPB), to examine consumer behavior toward STT (Herrmann & Kim, 2017; Jia & Kim, 2015; Melzner et al., 2014). Some studies have combined these models with specific theoretical constructions from the STT literature. For instance, Jia and Kim (2015) offer a **TPB-based model** that includes attitude, subjective norm, control of perceived behavior, and the influence of social media. They combine this model with the theory of **diffusion of innovation** (DOI). Their model is designed to understand the adoption of smartwatches, such as the Apple Watch.

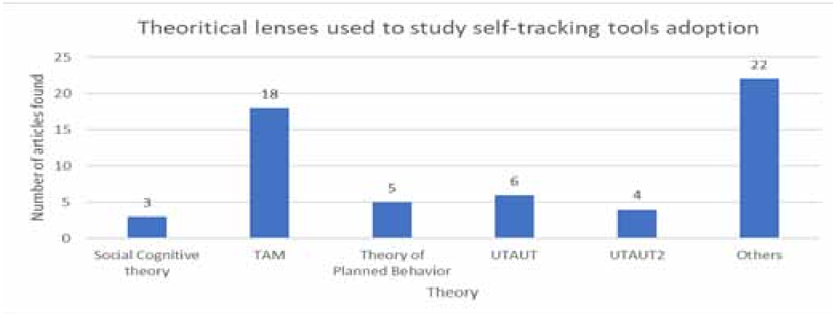
Moran et al. (2013) have built a model to compare the British and the Japanese adoption of ubiquitous surveillance devices. They use the TPB combined with attitude toward technology, as well as attitude toward apps, as an antecedent to attitude toward behavior and behavioral intention to use the technology.

The **technology adoption model** (TAM) has been created to explain why individuals accept technology in the workplace (Davis, 1989). Several researchers have extended the TAM-based model to explain STT adoption by accounting for technological and behavioral aspects (Gao et al., 2016; Kim & Shin, 2015; Lunney et al., 2016; Spagnolli et al., 2014). For example, to explain the adoption of smartwatches, Chuah et al. (2016, p. 278) have added a new variable, namely visibility, defined as “a person’s beliefs about the extent to which smartwatches are noticed by others (Fisher & Price, 1992).” Baudier et al. (2020) examined the variables impacting (or not) attitude towards using a smartwatch relying on the TAM and two additional variables, namely perceived connectivity and perceived usefulness.

Developed by Venkatesh et al. (2003), the **unified theory of acceptance and use of technology** (UTAUT) provides a unified view of eight models extensively used in IS, comprising the TPB and the TAM. Pfeiffer et al. (2016) have added a reflexive dimension to the UTAUT, which consists of trust, perceived aesthetics, and personal innovativeness, to study STT adoption. This addition is supposed to reflect the human-machine interaction better.

Introduced by Bandura (1986), the **social cognitive theory** (SCT) anticipates that individuals will become motivated and guide their actions through their beliefs and self-efficacy (O’Brien et

Figure 1. Frequency of occurrence of the prevailing adoption theories in the STT literature



al., 2015). The SCT is used in conjunction with other models to explain the behavior to maintain a physical activity or to encourage changing a behavior. Researchers relying on the SCT want to explain how STT leads to self-efficacy. For example, Ehlers and Huberty (2014) incorporate both the SCT and the UTAUT to examine user preferences for mobile physical activity apps. Self-regulation has emerged as a variable that improves physical activity.

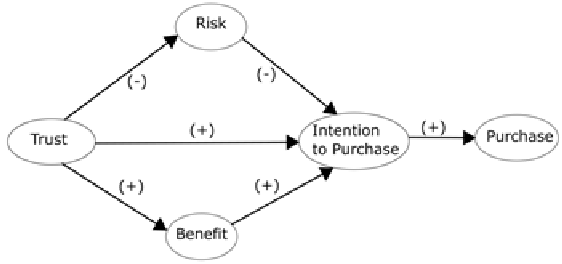
The literature shows a wide variety of explanatory variables that do not belong to any of the categories commonly used in the IS literature, but they appear in other fields, such as user experience modeling. The STT literature is transversal, so it includes many theories from psychology or medicine, with theories on motivation (Gimpel et al., 2013; Shin & Biocca, 2016), the theory of persuasion (Shih et al., 2015), and the self-efficacy of technologies in behavioral change (Park et al., 2015). Beyond the adoption of technologies, researchers also question the usefulness of STT for health and wellbeing management, which are the top promises made by manufacturers of self-tracking devices. For instance, Shin and Biocca (2016) use the Transtheoretical Model (TTM) and the **expectation confirmation theory** (ECT) to explain pre and post-adoption. The TTM is generally used to explain why an individual changes one's behavior. Figure 1 summarizes the frequency of occurrence of the five prevailing adoption theories that appear in the literature analysis.

Appendix A shows that very few studies have mobilized technological, medical, and social aspects together. Appendix B represents the variables' ranking: ease of use, utility, and standards are the most common themes in the literature. Attitude toward technology and behavioral intention to use ST tools are widely used variables. This underlines the importance of TAM in the analysis of STT acceptance. Due to space limitations, Appendix B is restricted to the most cited variables in a maximum of three publications. Several constructs have only been found once or twice in the literature. This volume corresponds to 121 variables from a total of 144 variables. Taking into account the significant variables found in the 75 articles, the researchers have done a two-level classification that can be found in Appendix C. The first level contains three themes: 1) the tool's characteristics and user perceptions of these characteristics, 2) the person's characteristics, and 3) social concerns. At the second level, we specified sub-dimensions and the number of variables used in the literature.

4 THE CONCEPT OF RISK IN IS RESEARCH

Risk is a concept that is studied in many different disciplines, such as economics, psychology, or marketing (Bauer, 1967). In IS, risk is often used to explain IS usage or intentions to use them, for example, in e-commerce (Doolin et al., 2005, Dinev et al., 2006, Mou et al., 2020), because this variable has a significant influence on user perceptions (Cocosila et al., 2009; Featherman & Pavlou, 2003). Actually, technologies can be compared to a black box whose content is unknown to the user because the information is sometimes unavailable to explain the functioning of the technology. This

Figure 2. Extended Valence Framework (Kim et al., 2009, p. 239)



lack of information translates into a perceived risk for users (Cocosila et al., 2009). Moreover, IS raises security issues, whether they occur during an electronic transaction when paying on a merchant's website (Dinev et al., 2006; D. J. Kim et al., 2008; Y.-H. Li & Huang, 2009; Lian & Yen, 2014; Verhagen et al., 2006) or when using an online service (Horst et al., 2007; M.-C. Lee, 2009; Martins et al., 2014). These risks are generally measured with six dimensions (see Appendix D), such as privacy risk or source risk, that is, the risk related to the lack of knowledge of the seller's reputation (Lim, 2003). Risk is a concept that can be found in many IS articles, of which a few examples is cited in Appendix E.

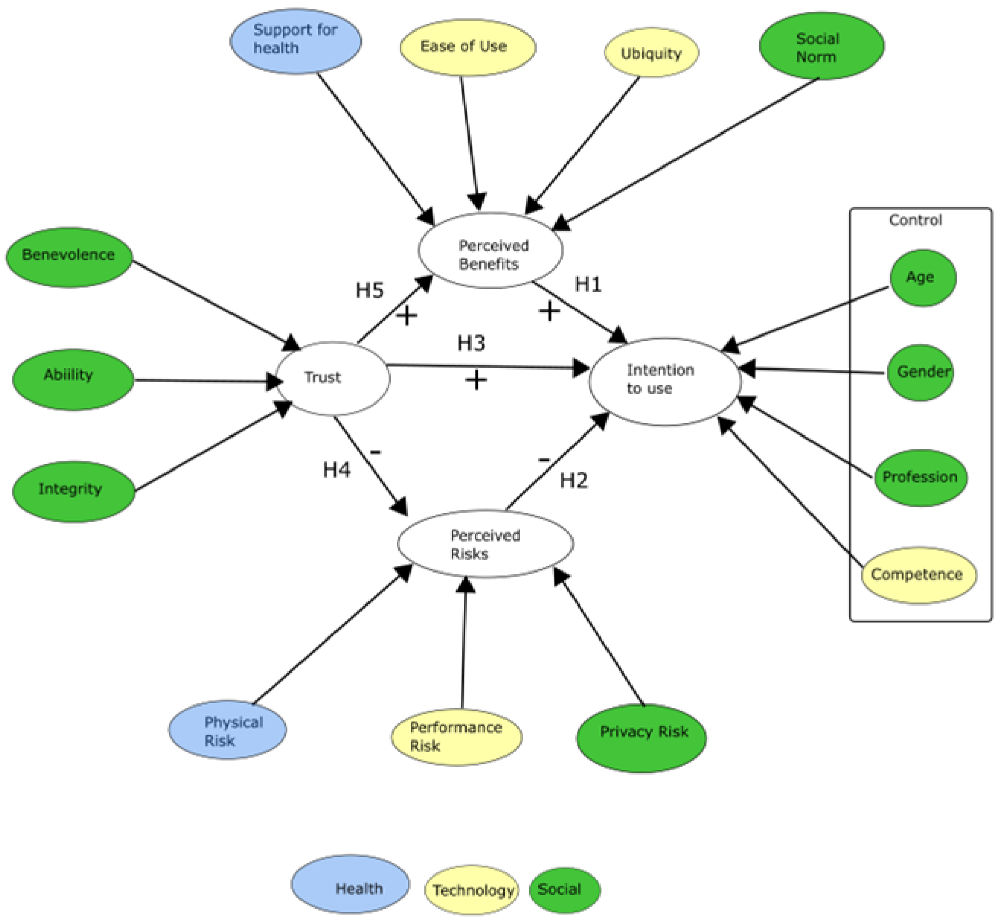
To analyze the role of risk, some researchers rely on the valence theory (Peter & Tarpey Sr., 1975). According to Kahneman and Tversky (2013), this theory originates from the established school of thought, named the rational choice theory, which considers that individuals act in accordance with a utilitarian logic based on the evaluation of costs and benefits. After doing calculations, individuals evaluate the costs and the benefits of the solutions considered in order to maximize their overall benefit. This theory has been used in IS to explain user behavior in a variety of situations, such as the perception of security information or the choice of a password (Aytes & Connolly, 2004; Bulgurcu et al., 2010). These cited authors explain that complying with the rules tends to produce benefits, while non-compliance can lead to costs. Lee (2009) has developed a model based on the valence theory to measure technology adoption in an e-trading context. The perceived security risk of banking transactions is balanced by the perceived benefit of using an online service that reduces transaction costs and allows greater responsiveness.

Kim et al. (2009) have extended this theory in the marketing context to account for the role of trust in risk/benefit evaluation and to measure the impact on customer intentions (see Figure 2). Mou et al. (2016) have relied on this extended version of the valence theory in conjunction with the Health Belief Model (Rosenstock, 1974) to theorize the adoption of online health services. Mou et al. (2016) define risk as the sum of performance-related risks, psychological risks, and perceptions on the time needed to search for health information. This sum of risks is counterbalanced by the consumer belief that online health information could improve one's health condition (perceived benefits). Their results confirm that the benefits positively influence the intention to use ST tools and that the risks negatively affect the adoption of digital health services. Their results also prove the role of trust in positively influencing intentions, reducing risk perceptions, and increasing perceived benefits.

5 DEVELOPING THE THEORETICAL MODEL

Drawing on the Extended Valence Framework and the literature review on the risks and the benefits of STT adoption, a comprehensive research model has been developed (Figure 3). This section presents the hypotheses by explaining the assumptions that have led to the construction of this model. It is hypothesized that trust will influence individuals' perceptions of risks and benefits and

Figure 3. Research model



their intentions to use the technology. Perceived benefits comprise health support, ubiquity, ease of use, and social norms, which all have a positive impact on the intentions to use STT. Perceived risks include physical, performance, and privacy risks. The risks and the benefits that are integrated into the model represent the most salient factors identified in the literature. They also cover well the three dimensions (health, social, and technological) presented in Figure 3 below.

5.1 Perceived Benefits

Two technological factors are retained to measure perceived benefits, namely perceived ease of use and ubiquity. Perceived ease of use refers to "the extent to which the potential user expects the target system to be free of any user effort" (Davis, 1989, p. 320). Prior research has demonstrated the positive effect of ease of use on the intention to use STT (Lunney et al., 2016; Pfeiffer et al., 2016). A qualitative study also highlights users' need for simple and easy to use STT (Canhoto & Arp, 2017). Following this reasoning, it can be assumed that this factor is a component of perceived benefits and can encourage the intention to use STT. Since STT belongs to the category of mobile technologies, users will generally expect mobile features or the possibility to have a ubiquitous

Table 2. Benefits of self-tracking

Dimension	Factor	Articles
Health	Disease management	(Swan, 2009; Majmudar et al., 2015 ; Becker, Matt, Widjaja, & Hess, 2017)
	Assistance to the elderly	(Majmudar et al., 2015)
	Self-awareness	(Choe et al., 2015 ; Sharon et Zandbergen, 2017)
	Support for Physician-patient communication	(Ruckenstein, 2015; Majmudar, 2015)
	Increase physical activity	(Barret et al., 2013 ; Pfeiffer et al., 2016)
	Increase one' s potential	(Lupton, 2013 ; Swan, 2013)
	Self-control	(Lupton D. 2014; Pfeiffer et al. ,2016)
Social	Motivation through data sharing	(Swan, 2009; Stragier et al., 2015)
	Social acknowledgement through self-management, and self-image	(Lupton, 2015; Crawford et al., 2015; Mercer K. et al. 2016 ; Becker et al., 2017 ; Peng et al., 2016 ; Chuah et al., 2016)
Technology	Ease of use	(Canhoto & Arp, 2017 ; Lunney et al., 2016) (Melzner et al., 2014 ; Chuah et al., 2016)
	Ubiquity	(Gimhae, 2013; Kim & Shin, 2015; Jung et al., 2016; Hirose & Tabe, 2016 ; Gribel et al., 2016; Neill et al., 2016)

experience. Ubiquity is characterized by time and space flexibility and defined as the opportunity "to monitor user conditions anytime and anywhere" (Hirose & Tabe, 2016, p. 48; see aksi Okazaki et al., 2009). Ubiquity positively influences users' perceptions when they use STT (Hirose & Tabe, 2016; Kim & Shin, 2015) and contributes to the perceived usefulness of the wearable device (Gribel et al., 2016). Therefore, ubiquity is another component of perceived benefits.

The various health-related benefits can be combined into a single variable called health support, defined as "the perception of portable self-care devices to support the treatment of health problems" (Pfeiffer et al., 2016, p. 6). Indeed, the intrinsic objective of ST, as given by its definition, is to improve health. Besides, monitoring one's health is one of the main reasons for explaining the purchase of STT devices (M. Becker et al., 2017). Therefore, health support represents an important sub-construct to assess perceived benefits.

Lastly, perceived benefits include social benefits, namely social norms, defined as "the extent to which consumers believe that other important people (e.g., close friends and family) believe they should use a particular technology" (Venkatesh et al., 2012, p. 159). This factor has been extensively tested in the research stream of technology adoption. Social norms originate from the TPB and describe the social pressure to behave in a certain way (Ajzen, 1991). Past research indicates that ST practice is a response to social pressure (M. Becker et al., 2017; Crawford et al., 2015; Peng, Kanthawala, et al., 2016) and that this social pressure positively influences the intention to use STT (Gilbert & Namagembe, 2013; Pfeiffer et al., 2016; Yoganathan & Kajanan, 2014).

The benefits of self-tracking are summarized in Table 2.

These three different benefits, combined together, constitute an overall perception of the perceived benefits, which positively influence the intention to use STT, in accordance with the Extended Valence Framework (Kim et al., 2009; Mou et al., 2016). Therefore, the following hypothesis was posited:

H1: Perceived benefits positively influence the intention to use STT.

5.2 Perceived Risks

Performance risk is defined as "the possibility that the product will malfunction and not function as designed and advertised and, therefore, fail to provide the desired beneðt" (Grewal et al., 1994, p. 145). Thus, when the STT is not representative of someone's own activity, one will stop using it (Buchwald et al., 2015; Wen et al., 2017). Additionally, some tools lack the ability to automatically detect user activity (for example, practicing a sport, sitting, or sleeping is not always captured well by the technology). This leads to the manual entry of the data, which is time-consuming and tends to have a negative impact on ST practices (Almalki et al., 2015). As such, the lack of performance contributes to a perceived risk of using monitoring tools.

The different health risks can be combined into a single variable named physical risk, which is defined as "the possibility that products may be harmful to the health of individuals or those products may not look as good as individuals expect" (Lim, 2003, p. 219; see also Jacoby & Kaplan, 1972). It can be operationalized in terms of wearable discomfort (M. Becker et al., 2017; Shih et al., 2015) or techno-stress (Spagnolli et al., 2014). Consequently, the perceived physical risk is a factor that negatively affects the intention to use ST.

The third risk that is frequently mentioned in the literature is the privacy risk, which is defined as "potential loss of control over personal information, for example when information about you is used without your knowledge or permission" (Featherman & Pavlou, 2003, p. 455). This risk is amplified by the fact that ST data tend to be hosted on the cloud (Lupton, 2015), making it vulnerable and reusable by third parties. For example, health and wellbeing apps available in ST devices share or exchange data with third parties, and several large insurance companies are also partnering with health app developers (Dredge, 2013). Privacy risk represents an additional attribute of perceived risk.

The risks of self-tracking are summarized in Table 3.

These combined three risks reflect an overall perception of the perceived risks. In accordance with the Extended Valence Framework (D. J. Kim et al., 2009; Mou et al., 2016), the authors posit the second hypothesis:

H2: Perceived risks negatively influence the intention to use STT.

5.3 Trust

Trust is defined as "the belief that the other party will behave in a socially responsible manner, and, by so doing, will fulfill the trusting party's expectations without taking advantage of its vulnerabilities" (Pavlou, 2003, p. 74; see also Gefen, 2000). Research has shown that this variable is often associated with different risks that influence the intention to use technologies (Gao et al., 2016; Mou, 2015). As such, ST research has consistently identified trust as playing a role in ST adoption (Greenfield et al., 2016; Shih et al., 2015), but few studies have used it in quantitative models (e.g., Jusob et al., 2016).

Due to the fact that self-monitoring systems continually collect data from users, the latter needs to trust the provider, especially its ability to guarantee data security (Gefen et al., 2003). Trust has been questioned several times when examining ST (Altenhoff et al., 2015; Gao et al., 2016; Pfeiffer et al., 2016). This is mainly due to a certain opacity of manufacturers that rarely explain their methodology to detect and measure physical activities (Shih et al., 2015). Users will often triangulate with physicians to validate the effectiveness of their monitoring applications (Peng, Yuan, et al., 2016). Conversely, users who do not trust the data collected by ST devices tend to reject the technology and to favor assessments conducted in the hospital (Sun & Rau, 2015).

In the Extended Valence Framework (Kim 2009) and in studies on monitoring tools (Gao et al., 2016; Jusob et al., 2016; Mou et al., 2016; Pfeiffer et al., 2016), trust is a variable that directly affects the intention to adopt ST devices. Consequently, the following hypothesis was posited:

Table 3. Risks of Self-Tracking

Dimension	Factor	Article
Health	Techno-stress	(Spagnolli et al., 2014)
	Vulnerability to disease	(Gao et al., 2015; Melzner et al., 2014)
	Impact from disease	(Becker et al., 2017 ; Melzner et al., 2014)
	Discomfort	(Shih et al., 2015 ; Becker et al., 2017)
Social	Privacy	(Mackert et al., 2016 ; Illiger et al., 2014 ; Guo et al., 2012 ; Greenfield et al., 2016 ; Jusob et al., 2016 ; Su & Rau, 2015 ; Cheng & Mitomo, 2017 ; Li et al., 2016
	Trust	(Shih et al., 2015 ; Buchwald et al., 2015 ; Jusob et al. 2016 ; Peng et al., 2016 ; Yoganathan & Kajanan, 2014 ; Altenhoff et al., 2015 ; Gribel et al., 2016 ; Pfeiffer et al., 2016 ; Sun & Rau, 2015 ; Gao et al., 2016)
	Third-Party Surveillance	(Lupton, 2013; Ruckenstein et Schüll, 2017)
	Normalization	(En et Pöll, 2016)
Technology	Waste of time in data management	(Rapp et Cena, 2016 ; Almalki et al., 2015).
	Data reliability	(Becker et al., 2017; Coorevits & Coenen, 2016; Shih et al., 2015; Buchwald et al., 2015; Wen et al., 2017)

H3: Trust positively influences the intention to use STT.

The valence model also points out the effects of trust on perceived benefits and perceived risks. For instance, users of monitoring tools express the role of trust in risk perception (Gribel et al., 2016). In other areas, such as e-commerce, the higher the confidence in the seller, the lower the perceived risk appears to be (Gefen et al., 2003). This leads to the following hypothesis:

H4: Trust reduces perceived risks.

E-commerce studies show that trust positively influences a product's perceived usefulness (e.g., Gefen et al., 2003). More precisely, the more credible the seller's image is, the more the buyers perceive the promise of a perceived benefit. According to Mou et al. (2016), trust also influences the perceived benefit of using online health services, hence the following hypothesis:

H5: Trust increases the perceived benefits of using STT.

6 METHODOLOGY AND DATA COLLECTION

6.1 Scale Measurement

The measurement scales were developed relying on the literature. The items were then modified to fit the ST context. All constructs were measured with at least three indicators and a 7-point Likert scale, which is more reliable than the 5-point scale (Maydeu-Olivares et al., 2017). Intention to use STT was measured with the scale that Pfeiffer et al. (2016) employed in their ST study. For trust, the authors chose a three-dimensional formative construct inspired by Mayer et al. (1995) and used by Mou and Cohen (2014) in the context of online health services.

Health support was measured with the scale developed by Pfeiffer et al. (2016). The items cover health awareness, disease prevention, and stimulation of physical activity to maintain a healthy lifestyle. We added cognitive support, which contributes to people's good health. Ubiquity was measured using the scale employed by Hirose and Tabe (2016) based on that of Okazaki and Mendez (2013). Ease of use was measured with the scale used by Pfeiffer et al. (2016) based on those of Venkatesh et al. (2003), Lu et al. (2005), and Gefen et al. (2003). Social influence was measured using the scale of Pfeiffer et al. (2016) based on that of Venkatesh et al. (2012). These items introduce the notion of sharing and comparing ST data as motivators (Stragier et al., 2015).

The physical risk was measured with the scale employed by Gurtner (2014). Based on the work of González Mieres et al. (2006), the scale was used by Gurtner (2014) in a study on resistance to mobile health applications. Performance risk was measured with the scale applied by Yang et al. (2016). Used in the adoption of wearables, this scale was based on those of Grewal et al. (1994) and Stone and Grønhaug (1993). Privacy risk was measured with the scale of Li et al. (2016), who used it for the adoption of health wearables. The survey is shown in Appendix F.

6.2 Second-Order Concepts

The risk model is based on three second-order formative constructs (C. Ringle et al., 2015) representing profit, risk, and trust. To operationalize them, we use a two-step approach called the "sequential method of repetition score of the factors that compose the latent variables" (Becker et al., 2012; Ringle et al., 2012). The first step is to add the set of first-order manifest variables to the second-order latent variables, as shown in Appendix G. In the second step, the model is computed, and the scores of the latent variables are recorded in a file. A new model is created, containing only the second-order latent variables. The score of the first-order variables is used as the formative manifest variables for the second-order latent variables (Appendix H). This method generates the value of R^2 and indicates the influence of the other variables (J. Hair et al., 2016).

6.3 Data Collection Procedure

The authors conducted an online survey from two different sources. A portion of their sample came from Facebook. Using a social network has the advantage of returning a wide range of profiles through the snowball mechanism (Biernacki & Waldorf, 1981) in a relatively short period of time. The questionnaire was posted online from November 1st to November 30th, 2018, and received 210 responses. The second data source was a European university, where the authors administered the questionnaire to 118 students. They, therefore, received a total of 328 responses. Having these two different sources for data gathering offers more diversity in terms of the age range. The questionnaire began with a description of the tracking tools and cited examples of products, such as Fitbit and Apple Watch. The data were analyzed using SmartPLS software. The researchers followed the recommendations (Gefen et al., 2000) on a sample size at least ten times larger than the size of the most complex construct. In their model, perceived benefit represents the most complex construct. It is composed of 18 items, forcing us to have a minimum of 180 responses.

7 DATA ANALYSIS

The data were filtered to keep only those questionnaires that were completed in their original form. As a result, 83 questionnaires were deleted. Then, we removed all the questionnaires from the respondents with no knowledge of self-monitoring technologies. Nine questionnaires were thus withdrawn. The usable sample consists of 236 questionnaires in total.

The authors employed SmartPLS 3.0 software to analyze the data (C. Ringle et al., 2015). Several reasons led us to favor the Partial List Squares technique. First, the model is composed of formative constructs. This type of construct is particularly adapted to a PLS approach. Second, the model is complex due to its 11 constructs. Finally, the size of our sample is small, and the data do not respect a normal distribution.

7.1 Descriptive Analysis

The descriptive analysis of the sample indicates a greater presence of women (62%) than men (38%) (Table 4). The average age is relatively young (31 years old), due to half of the sample comprising first-year bachelor's degree students. Users represent 27% of the entire sample, that is, nearly 3 out of 10 individuals, which should be compared with market statistics, that is, 12% of the French own a connected bracelet or watch (OpinionWay, 2017). The results are, therefore, comparable with those of the market. Among the technologies, mobile apps are the most widely used, with 27% of the people reporting having used a mobile app.

7.2 Data Distribution

Although PLS is a method that does not require a "normal" distribution of data, it is still recommended to check that the distribution should not deviate excessively from the normal range (J. Hair et al., 2016). To test the validity of the distribution, Hair et al. (2016) suggest checking that the skewness indicator (skewness of the distribution) and the kurtosis indicator (width of the distribution) remain within a value between -1 and +1. When the skewness indicator is greater than 1, it means that the distribution is skewed to the right, and when the indicator is less than 1, it means that the curve is skewed to the left. A kurtosis value greater than 1 means that the curve is too sharp, and a value less than 1 means that the curve is too flat. The table in Appendix D provides the indicator values for the different items. It shows that EOU2, EOU3, and UB1 are too narrow compared with a normal distribution. However, since the degree of kurtosis does not deviate much and since these items are part of a reflective scale that contains other items, this deviation is not considered a problem, so these items were retained.

7.3 Reliability and Validation of Scales

In the PLS approach, construct validity is generally measured by discriminant validity and convergence validation (Gefen & Straub, 2005). Convergence validity confirms that each item is correlated with the theoretical construct. Discriminant validity confirms that these items are weakly related to the other theoretical constructs. Several measurement techniques exist, and the authors follow Gefen and Straub's (2005) recommendation to verify both levels of validity.

Convergence validity (i.e., the estimate that an indicator is correlated with other indicators of the same construct) is assessed by the external load and the average variance extracted (AVE). Appendix I shows the different results. An indicator is considered representative if its T-value is greater than 1.96 and its load is greater than 0.7 (Hair et al., 2016; Nunnally & Bernstein, 1967). Only one item does not meet this threshold, namely item #2 of performance risk (PER2). According to the recommendations of Hair et al. (2016), the item can be removed if doing so improves internal reliability. After the removal of the indicator, the calculations show no improvement. The authors have therefore decided to keep it. The AVE values are between 0.539 and 0.867, which are above the recommended threshold of 0.5. This means that on average, the construct explains more than half of the variance of the indicators comprising it. The internal consistency of the constructs is tested with the reliability indicator (composite reliability). The results show values above the recommended threshold of 0.7.

For discriminatory validity, it is necessary to check that the indicators only represent the constructs to which they refer. Appendix J shows that all factors are defined only in their constructs and do not overlap with the others. Therefore, the results confirm the convergence of the items. Table 5 presents the discriminatory validity of the constructs of the Fornell-Larker test (Fornell & Larcker, 1981). The square roots of the AVE are in bold font on the diagonals. The other numbers represent the correlation

Table 4. Descriptive analysis of the sample

		N
Complete		245
Users (%)		87 (27%)
Non Users (% Yes)		158
Exploitable		236
Competence	**Extremely incompetent**	24
	Mid competent	26
	Slightly incompetent	15
	Neutral	88
	Slightly competent	36
	Mid competent	36
	Extremely competent	11
Mean Age (SD)		31 (15,5)
Male (%)		90 (38%)
Female		146 (62%)
Country	**France**	218 (92%)
	Other	18 (8%)
Profession	Artisan	10
	Higher intellectual profession	44
	Middle profession	30
	Employee	26
	Worker	4
	Student	111
	Other	7

between the latent variables. Discriminative validity is checked if the numbers on each row and column are less than the values in bold on the corresponding row or column. The cross-correlation table and the Fornell-Larker test confirm that the indicators represent only their constructs.

Podsakoff, MacKenzie, and Podsakoff (2012, p.565) explain that "method biases can significantly influence item validities and reliabilities as well as the covariation between latent constructs. This suggests that researchers must be knowledgeable about the ways to control method biases that might be present in their studies." To address the issue of common method bias, we tested for multicollinearity by calculating the variance inflation factor (VIF) values. We used in SmartPLS the full collinearity test by connecting all the latent variables to one variable (Kock, 2015). The results show that the VIF values are lower than the tolerated threshold of 3.3 at the factor level (ranging from 1.01 to 2.62), which indicates that multicollinearity is not an issue.

7.3.1 Second-Order Construction

We performed specific tests to evaluate the second-order constructs. Formative constructs are measured by the collinearity between the indicators and the significance and the relevance of the external weights

Table 5. AVE and correlation between latent variables

	1	2	3	4	5	6	7	8	9	10	11
1.Trust Ability	**0.82**										
2.Trust Benevolence	0.44	**0.93**									
3.Ease of Use	0.25	0.16	**0.84**								
4.Behaviour Intention	0.33	0.05	0.18	**0.93**							
5.Trust Integrity	0.70	0.6	0.26	0.23	**0.85**						
6.Social Norms	0.40	0.30	0.05	0.38	0.43	**0.75**					
7.Physical Risks	-0.13	-0.02	-0.15	-0.17	-0.08	0.20	**0.86**				
8.Private Risks	-0.03	0.08	-0.08	-0.21	-0.08	0.12	0.40	**0.92**			
9.Performance Risks	0.08	0.13	0.03	-0.02	-0.06	0.13	0.27	0.38	**0.73**		
10.Supprt to Health	0.50	0.36	0.18	0.42	0.36	0.45	0.04	0.06	0.13	**0.80**	
11.Ubiqity	0.33	0.22	0.61	0.32	0.31	0.17	-0.15	-0.11	0.03	0.33	**0.84**

(Hair et al., 2016). Contrary to reflexive constructs, it is not possible to directly suppress a manifest variable that would have low validity since it would require a theoretical justification.

In the first step, the collinearity between the indicators must be checked; that is, the correlation between the indicators. To assess the level of collinearity, Hair et al. (2016) recommend calculating the level of variance of the formative indicator that is not explained by the other indicators. On SmartPLS, this calculation is performed by the variance inflation factor (VIF). Table 6 shows the VIF results for the second-level formative indicators. A value greater than 5 indicates a collinearity problem (Hair et al., 2011), meaning that 80% of the variance is associated with the other indicators that comprise the formative construct.

The second step is the evaluation of the weight of each indicator. The weight expresses the contribution relation of the indicator to the construct. The question that then arises is to know whether the indicator actually contributes to defining the formative construct. This contribution can be relative or absolute. The absolute contribution, that is, the impact of the indicator on the construct without taking into account the other indicators, is given by the load. When a weight is not significant, but

Table 6. Collinearity factor between indicators

Second Order	First Order	VIF
Trust	Ability	1,938
	Integrity	2,616
	Benevolence	1,680
Benefits	Ease Of Use	1,587
	Social Norms	1,256
	Support To Health	1,361
	Ubiquity	1,715
Risks	Physical Risks	1,212
	Private Risks	1,312
	Performance Risks	1,194

Table 7. Weight and load of the indicators

Second Order	First Order	Weight	Loading	Weight T Stat.	Loading T Stat.	Significant weight	Significant Loading
Trust	Ability	0,804	0,982	5,407	29,824	Yes	Yes
	Benevolence	0,060	0,555	0,294	4,168	No	Yes
	Integrity	0,217	0,815	0,872	8,788	No	Yes
Benefits	Ease Of Use	0,118	0,412	1,137	4,205	No	Yes
	Social Norms	0,457	0,744	4,905	11,236	Yes	Yes
	Support To Health	0,519	0,840	4,496	13,889	Yes	Yes
	Ubiquity	0,288	0,606	2,994	7,530	Yes	Yes
Risks	Physical Risks	0,632	0,769	1,571	2,378	No	Yes
	Private Risks	0,667	0,740	1,913	2,574	No	Yes
	Performance Risks	-0,469	-0,042	1,074	0,118	No	No

the load is significant (> 0.5), the indicator is absolute. Table 7 shows that performance risk does not contribute to expressing risk.

7.4 Validity of The Structural Model

Once the validity of the scales was verified, we tested the validity of the internal model. According to Hair et al. (2016), we should ensure that no correlation exists between the constructs; that is, they all represent different concepts. Accordingly (as with the formative constructs), we tested the variance inflation factor (VIF). Table 8 presents the results. All VIFs are less than 5 and validate the independence of the construct. Moreover, with the VIFs being lower than 3.3, the model is free of common methodological bias (Kock, 2015).

7.4.1 Direct Effects

This section focuses on the relationships between the different latent variables and thus test the validity of the hypotheses. Table 9 presents path coefficients. As the results show, only benefit (B = 0.512) and risk (B = -0.232) have an influence on the intention to use STT. Trust influences the perception of benefit (B = 0.589) but has no significant impact on the perception of risk and the intention to use STT.

Age, gender, occupation, and skill level in the use of self-monitoring devices were included as control variables. Their potential effects on intention to use STT was tested. Both age (B = 0.201) and skill (B = 0.118) influence intention. Gender does not influence behavioral intentions. Similarly, Baudier et al. (2020) found no empirical evidence when testing the moderating role of gender on the relationships between perceptions and attitude towards using smartwatch. Finally, the model yields an $R^2 = 0.36$ for intention to use, an $R^2 = 0.35$ for benefit, and an $R^2 = 0.01$ for risk (see Figure 4).

Table 8. Collinearity factor of the structural model

	Benefits	Trust	Behaviour Intention	Risks
Benefits			1,580	
Trust	1		1,598	1
Risks			1,093	

Table 9. Summary of Path Coefficients and Reliability Levels

Link	Path	T Statistics	Hypothesis
Hypothesis			
Benefits -> Behaviour Intention	0.512	6.417	Confirmed
Risks -> Behaviour Intention	-0.232	2.4	Confirmed
Trust -> Behaviour Intention	-0.054	0.574	Not Confirmed
Trust -> Benefits	0.589	11.401	Confirmed
Trust -> Risks	-0.130	0.946	Not Confirmed
Control Variables			
Age -> Behaviour Intention	0.201	2.753	Influence
Competence -> Behaviour Intention	0.118	2.193	Influence
Gender -> Behaviour Intention	0.004	0.078	Does not Influence
Profession -> Behaviour Intention	0.126	1.762	Does not Influence

7.4.2 Indirect Effects

In addition to the calculation of direct effects, the authors checked the existence of benefit–risk mediating effects on the relationship between confidence and the intention to use STT. At the theoretical level, this means that an individual may have full confidence in the manufacturer, but this does not translate into an intention to use its product. In other situations, low confidence leads to high intention to use. The results presented in Table 10 show the indirect effects of trust on the intention to use mediated by risks and benefits.

From Table 10, it can be concluded that benefit plays a full mediating role between trust and intention to use.

Table 10. Indirect effects of trust on intent to use

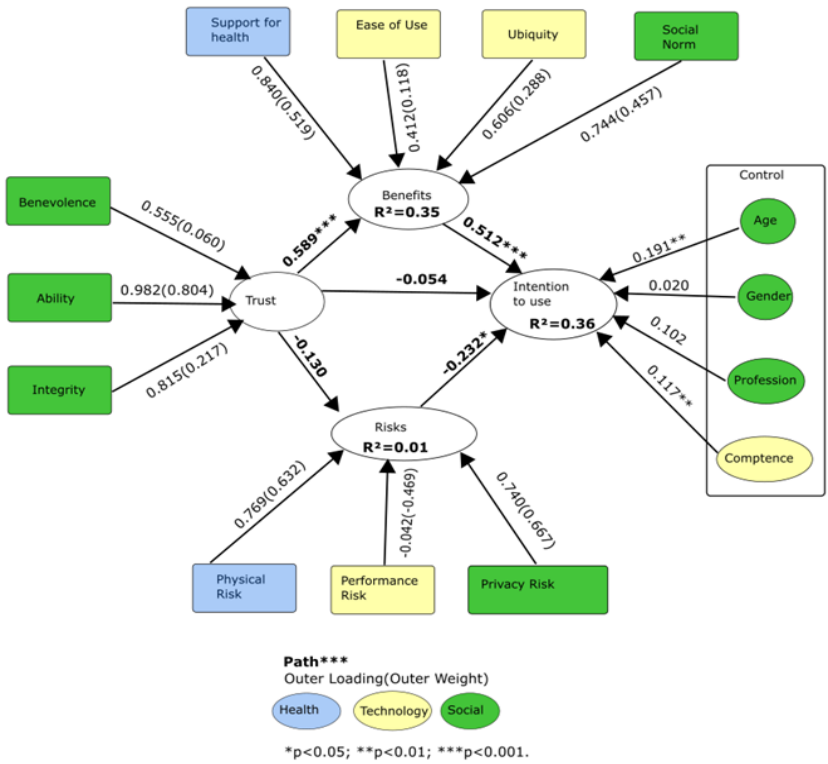
	Path	T Statistics	Confirmed
Trust -> Benefits -> Behaviour Intention	0,302	5,084	Yes
Trust -> Risks -> Behaviour Intention	0,030	1,244	No

7.5 The Effect of Unobservable Heterogeneous Groups

The authors performed a final test to assess unobservable heterogeneity. This test is still absent in existing IS studies (Becker et al., 2013; Fosso Wamba et al., 2017). Its application allows interesting conclusions to be drawn and avoids interpretation bias (Becker et al., 2013). The authors used the REBUS-PLS algorithm (Esposito Vinzi et al., 2008) implemented in XLSTAT-PLS version 2019.1.1 to detect the groups. They tested the reflexive version of the model since the algorithm only works in this mode. The execution of the algorithm allowed us to detect three groups of 88, 65, and 83 individuals, which is put back into the SmartPLS software to evaluate the three models. The results are presented in Table 11.

Table 12 shows the different R^2 values for each group. Class 1 and Class 3 validate four of the five hypotheses, but Class 3 leads to a much higher explained variance.

Figure 4. The path coefficients



7.6 Identification of Class 3

The authors cross-tabulated the different descriptive values of the study to identify the characteristics of individuals belonging to Class 3. They performed a chi-square test to verify the hypothesis that this class demonstrates the different characteristics.

They also performed a chi-square test between the class variable and each of the other variables taken separately and found a link between the class and the use of technologies. The question asked was as follows: "Have you ever used a self-monitoring device to monitor your health?" The "yes" answer is related to Class 1, while the "no" answer is more related to Class 3.

The authors segmented age into three classes: 0–25, 26–40, and > 40 and found a link with the classes. Class 1 is more related to the second age class, Class 2 is more related to the first age class, and Class 3 is more related to the third age class.

8 DISCUSSION

Three assumptions are validated. The ambivalence of risk versus benefit is verified. As a result, the model confirms that intention to use STT is influenced by both positive and negative user perceptions of STT (Kim et al., 2009; Mou & Cohen, 2014; Yang et al., 2016). However, the influence of benefits is much more important than the influence of risks. The same finding was reported by Yang et al. (2016) in their study on the intention to use wearables through a model of benefit versus risk

Table 11. Comparison of unobservable heterogeneous groups

	Class 1			Class 2			Class 3		
Link	**Path**	**T Stat**	**Hypothesis**	**Path**	**T Stat**	**Hypothesis**	**Path**	**T Stat**	**Hypothesis**
Hypothesis									
Benefits -> Behaviour Intention	0,513	3,378	**Confirmed**	0,498	2,505	**Confirmed**	0,565	5,265	**Confirmed**
Risks -> Behaviour Intention	-0,413	2,547	**Confirmed**	0,481	2,043	Not Confirmed	-0,282	2,408	**Confirmed**
Trust -> Behaviour Intention	-0,182	0,944	Not Confirmed	-0,522	2,169	Not Confirmed	-0,179	1,484	Not Confirmed
Trust -> Benefits	0,513	3,909	**Confirmed**	0,701	7,682	**Confirmed**	0,704	12,324	**Confirmed**
Trust -> Risks	-0,437	2,526	**Confirmed**	0,776	15,167	Not Confirmed	-0,563	6,808	**Confirmed**
Control Variable									
Age -> Behaviour Intention	0,089	0,693	No effect	-0,008	0,078	No effect	0,256	2,174	**Positive effect**
Competence -> Behaviour Intention	0,085	0,859	No effect	0,015	0,117	No effect	0,129	1,362	No effect
Gender -> Behaviour Intention	0,083	0,904	No effect	-0,079	0,668	No effect	0,036	0,467	No effect
Profession -> Behaviour Intention	0,0473	0,344	No effect	-0,060	0,531	No effect	0,126	1,256	No effect

Table 12. R^2 for each class

	R^2 class 1	**R^2 class 2**	**R^2 class 3**
Benefits	0,26	0,49	0,50
Behaviour Intention	0,37	0,36	0,56
Risks	**0,19**	**0,60**	**0,32**

assessment. According to the authors, this result can be explained by the fact that individuals already have experience with innovative mobile devices, such as smartphones. As such, they feel comfortable with these products and are therefore accustomed to their risks. According to Rogers (1962), new adopters are the ones who are willing to take more risks to test the technology.

Among the perceived benefits, health support carries significant weight. This shows that mentalities are changing and that monitoring tools are no longer perceived as gadgets. According to a survey conducted for Unicancer (Ticsante, 2017), the French are making progress in their perception

Table 13. Contingent table between classes and usage

	Usage		Residual	
	Already used	Never Used	Already used	Never Used
Class #1	54	34	3.78	-2.89
Class #2	15	50	-1.83	1.39
Class #3	18	65	-2.27	1.74

of connected health. They are more likely to view it as an opportunity to improve care (76% in 2017 versus 67% in 2015) and to prevent disease (82% in 2017 versus 78% in 2015) (Ticsante, 2017). The perception of a mature technology capable of assisting the individual in managing one's health is reinforced by the low weight of performance as a risk. While research has identified measurement variations among different products on the market (An et al., 2017; Gruwez et al., 2017; Lee et al., 2017; Price et al., 2017), individuals do not appear to be sensitive to the reliability of the tool. Another hypothesis would be that potential users do not expect to have a tool that does not work satisfactorily. Similarly, ease of use bears little weight on perceived benefit. The same finding is reported in a study of fitness tools (Lunney et al., 2016). This would be explained by the fact that users have now acquired sufficient experience and skill with the technology (Wang et al., 2014). In addition, half of the sample consists of digital natives who are much more comfortable with new technologies (Vodanovich et al., 2010): These individuals have an aptitude for learning new technologies and use them in a very natural way.

Social norms also play an important role in perceived benefits. Connected watches and fitness trackers are often gifts from people who care about the recipients' health and wellbeing. In communities, such as runners, an athlete tends to imitate others in order to fit in. If all runners have connected watches to keep track of their heart rates, the individual tends to buy a similar connected watch to be able to compare oneself to others.

Concerning the risks, the physical injury caused to the individual by the tool is perceived to be a major risk, as well as the risk of the violation of privacy. Gurtner (2014) points out a similar result of his study on mobile health apps, where he cites the example of medical information and recommendations delivered by the app that can lead the individual to act against one's health. There is also the risk of the wearable object itself, in direct contact with the individual's body. The results confirm the research interest in addressing privacy issues.

As opposed to other studies that have used the extended valence model, trust has no influence on the intention to use STT. The impact of this factor has been validated several times in the use of self-monitoring tools (Gao et al., 2016; Pfeiffer et al., 2016). However, confidence can have several different constructions. In the study by Gao et al. (2016), it refers to the reliability of measurements and a certain quality (Gefen et al., 2003). For Pfeiffer et al. (2016), it consists of vendor reliability,

Table 14. Contingent table between age and usage

	Age			Residual		
	0-25	26-40	>40	0-25	26-40	>40
Class #1	37	26	25	-1.35	2.73	-0.28
Class #2	48	5	12	2.36	-1.87	-1.70
Class #3	39	10	34	-0.69	-1.16	1.80

data storage security, and invasion of privacy. In this study, trust is based on the manufacturer's benevolence, ability, and integrity, as in the model of e-health adoption (Mou et al., 2016).

Although trust does not play a direct role in intention to use, the results show that benefit mediates this relationship. It is only through benefit that trust increases intention to use. Among the dimensions of trust, ability plays an important role. The indicators that comprise this construct emphasize the tool provider's ability to help the individual manage one's health; thus, ability is akin to health support (see Appendix E for the direct and the indirect effects of ability on the dimensions of benefit). The perception of the provider's skill increases the perceived benefit in managing an individual's health and therefore increases the intent to use. Integrity plays a direct role in performance risks. The more the provider is perceived as having integrity and being able to provide quality data, the more the performance risk is mitigated (see Appendix E).

Finally, age and skills (control variables) influence intention to use.

9 IMPLICATIONS

9.1 Theoretical Implications

This research contributes in several ways to IS research and more precisely to the sub-stream of IS adoption. First, while prior research on IS adoption has mainly applied the TAM (Davis 1989) as noted by Lee et al. (2003), we encourage IS researchers to explore more relevant models to study STT. Indeed, the TAM seems to offer a limited contribution to the examination of STT adoption because ease of use (a key variable of TAM) tends to be inherent of STT since only 5% of the respondents consider a self-monitoring tool difficult to use. Actually, ease of use of emerging technologies (e.g. sensors or chatbots) may indeed gradually lose its relevance in favor of other variables, such as interactivity and quality of communication with the tool (Vodanovich et al., 2010; Go and Sundar, 2019). Go and Sundar (2019) showed that anthropomorphism, message interactivity and identity cues tend be expected from users of chatbots. Vodanovich et al. (2010) also noticed that the joint development of digital natives, people who have grown up in a digital world, and ubiquitous technologies require a paradigm shift. This study confirms the suitability of the Extended Valence Framework to examine STT adoption. This model has already been used in e-commerce (Kim et al., 2009) and e-health services (Mou et al., 2016) contexts, but not yet in STT context. Therefore, we encourage IS researchers to continue extending the Valence Framework. More recently, Turel et al. (2020, p.1) also pointed out the rise of a digitized self, defined as "users who use at least one digital technology in their non-work life domains", which requires a socio-technical perspective. These different calls should invite IS researchers to diversify their theoretical backgrounds to study STT.

Second, the risk/benefit model is based on the technical, social, and medical dimensions of STT that have been repeated throughout the literature on self-quantification; as such, it enriches previous conceptualizations. We have identified the various perceived risks and benefits that influence STT adoption. The findings indicate that social norms and privacy are important predictors of intentions to use. This finding supports prior research (De Moya and Pallud, 2020, Kang & Jung, 2020). For instance, De Moya and Pallud (2020) showed that anonymous surveillance enabled by STT represents a source of disempowerment for users and a real concern that can influence continued usage. Surprisingly, the technical dimension, which is highly present in the literature, does not emerge as fundamental in this study. The analysis enables a critical reflection on the factors to be considered when designing STT tools and could inspire academics conducting Design Science Research (Hevner et al. 2004).

9.2 Managerial Contributions

This research has several management implications. The prevalence of health factors and potential threats to the body and privacy should guide manufacturers in adopting new product development strategies. In the near future, we should witness the emergence of standards that are closer to medical standards so that these tools would finally shift away from gadgets and become aids to diagnosis and medical monitoring. This data accuracy will need to be complemented by clear security and privacy policies. Closeness with the medical world should be boosted by the emergence of medical data storage systems. For example, since 2018, the French postal service has offered a new health application that facilitates the sharing of personal health data (such as ST) with the medical profession. Recently, Fitbit inc. launched a study conducted with the users of its wearables to contribute to the early detection of COVID-19 and the flu (Etherington, 2020).

Thus, in the medium term, there should be a convergence of medical and ST data. Manufacturers should then work more on storage solutions that are secure yet open enough to allow exchange with other applications. We advise designers to take this aspect into consideration and vendors to communicate their ability to maintain user security and privacy. For instance, Apple does it for its health app that stores Apple Watch data (Apple, 2018), as can be read on their website (www.apple.com/ios/health/).

Furthermore, with COVID-19, several countries such as Singapore, South Korea, and France have developed and sometimes enforce the usage of a mobile application to encourage citizens to signal any early symptoms. However, Rowe et al. (2020) examined the French Stop-COVID app and showed that the coercive communication adopted by the French government to promote the app generated distrust and low adoption rates. Actually, the alienating context and the flawed design of the app contributed to its low deployment. Thus, Rowe et al. (2020) insist on the importance of collaboration across disciplines and fields of expertise to design less alienating apps. The design of STT also requires collaborative teams of experts and scientists to better acknowledge the impacts of these technologies on people's life and to reduce their potential risks.

10 LIMITATIONS AND CONCLUSIONS

Despite all the care and attention paid in that study, it reveals certain limitations. First, the questionnaire consists of a large number of constructions, which makes it time-consuming to complete. As a result, the authors have been confronted with a high dropout rate. The sample is therefore limited to 236 respondents. The presence of different classes in the sample represents another limitation because it can to lead to significant variations in the results.

The second limitation concerns formative constructs. The analysis shows that performance risk is only marginally involved in risk formation. Additionally, although a model comprising second-order constructs is more elegant and avoids many links, it also hides certain relationships, as shown in the table in Appendices G and H.

Taking over existing constructs to adapt them to a specific context is also a limitation. Indeed, the questions may seem too generalist, as is the case for performance risk and trust.

Finally, we believe that it would be more effective to introduce the tool through demonstrations in order to allow the layperson to try out the system for a few days. In that way, an individual can identify the usefulness of the tool and its dangers, thereby reducing the inequalities in risks between those who are knowledgeable and those who lack knowledge (Cooper, 2008).

In conclusion, this paper proposes a new model for assessing the intention to use ST tools. The results show that the individual performs a benefit-versus-risk calculation. However, the risks that we have identified seem to be much less important in relation to the benefits that the tool can bring in terms of health and social image. That study is the first to show that health support is an important factor in self-monitoring tools. Furthermore, it indicates that trust plays a role in perceived benefits and has an indirect influence on the intention to use ST tools. Finally, the research suggests that self-monitoring tools should be approached from a perspective that is close to medical standards in order to provide important benefits in managing an individual's health.

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APPENDIX I.

The Three dimensions of ST in the models

Table 15.

Authors	Technological	Medical	Social
(Baumgart & Wiewiorra, 2016)	X	X	
(Cho et al., 2015)	X	X	X
(Choi & Kim, 2016)	X		
(Choi et al., 2017)	X	X	X
(Chuah et al., 2016)	X		X
(Deng et al., 2014)	X	X	X
(Ella Carter, 2013)	X		
(Fensli et al., 2008)	X	X	
(Gao et al., 2015)	X	X	X
(Gao et al., 2016)	X		X
(Gilbert & Namagembe, 2013)	X		X
(Hirose & Tabe, 2016)	X	X	X
(Hoque & Sorwar, 2017)	X		X
(Hsiao & Chen, 2017)	X		X
(Huang & Lai, 2016)	X		
(Kim & Shin, 2015)	X		X
(Lee et al., 2017)	X	X	
(Li et al., 2016)	X		X
(Lunney et al., 2016)	X		X
(Maltseva & Lutz, 2018)			X
(Marakhimov & Joo, 2017)		X	X
(Mital et al., 2017)	X		X
(Ogbanufe & Gerhart, 2017)	X		
(Okumus et al., 2018)	X		X
(Park et al., 2015)	X		
(Pfeiffer et al., 2016)	X	X	X
(Prayoga & Abraham, 2016)	X		
(Song et al., 2017)	X		X
(Spagnolli et al., 2014)	X		
(Su & Gururajan, 2010)	X		X
(Wu et al., 2011)	X		X
(Wu et al., 2016)	X		X
(Yang et al., 2016)	X		X
(Yoganathan & Kajanan, 2014)	X		X
(Yuan et al., 2015)	X		X
(Zhang et al., 2017)	X	X	X

APPENDIX II.

The Main Variables From The Models

Table 16.

Theoretical constructs	Definition	Article counts	Associated adoption theories
Perceived usefulness	Perceived usefulness can be defined as the extent to which a person believes that using a particular system would be helpful and enhance performance (Davis,1986)	32	TAM
Perceived ease of use	Perceived ease of use refers to the degree to which the prospective user expects the target system to be free of effort in use (Wu et al. 2011)	23	TAM
Subjective norms	Subjective norms illustrate how others impact one's motivation to exercise or live a healthy lifestyle, and, as a result, adopt a WFT device (Lunney et al. 2016)	14	TRA
Behavioral intention	Behavioral intention is a measure of the strength of one's willingness to try and exert while performing certain behavior. (Wu et al. 2011), The user's desire to accept a particular system(Davis 1989)	18	TRA
Attitude towards actor behavior	The possibility of a user to accept a particular system (Davis, 1989)	11	TRA
Performance Expectancy	Performance Expectancy of fitness app is defined as the degree to which an individual believes that using the fitness app will help him/her to attain gains in physical activity performance or achieve physical activity goals. (Yoganathan et al. 2011)	11	UTAUT
Facilitating Conditions	Facilitating conditions are explained as factors in the environment that either facilitate or impede acceptance of technology (Venkatesh, 2000). Facilitating conditions are similar to the concept of perceived behavioral control in TPB. According to TPB, perceived behavioral control is derived from two sources: the external and the internal control (Ajzen, 1991)	10	UTAUT
Effort Expectancy	Effort expectancy is widely known as the degree of ease related to consumer'suse of technology (Venkatesh et al., 2012). In healthcare wearable device context, effort expectancy is introduced to measure consumer's perceived ease of using wearable devices in healthcare (Gao 2015)	9	UTAUT
Perceived behavioral control	Perceived behavioral control considers control beliefs and ability to influence these belief. Perceived behavioral control examines control over behavior and ability to influence behavior. In the case of technology, technology may be either a positive or negative control variable in that it may encourage or prevent exercise. (Herrmann et al. 2017)	8	TPB
Enjoyment		7	
Perception of Privacy		7	
Perception of Trust	The extent to which a person believes that using a particular system would be safe and high quality (Gefen et al. 2003)	7	
Attitude Toward Technology	a positive or negative view of the application of a technology (Moran 2013)	7	TAM
Hedonic Motivation	refers to the pleasure or enjoyment derived from adopting and using a technology (Venkatesh et al., 2012)	7	UTAUT2
Price Value		7	UTAUT2

continued on next page

Table 16. Continued

Theoretical constructs	Definition	Article counts	Associated adoption theories
Personal Innovativeness	personal innovativeness refers to the willingness of a potential user to try out new information technology since wearable self-tracking devices are a very new and relatively unknown technology (Pfeiffer et al. 2016)	6	
Self-efficacy	Self-efficacy is a set of beliefs one has about his/her ability to organize and complete a task in order to accomplish a certain task that is crucial for eliciting health behavior change [22] (Bandura 1977)	6	SCT
Compatibility	the degree to which wearable devices comply with other products' (e.g., smartphones, PCs) technical functionalities, users' business needs and lifestyles (Yu et al. 2016)	5	DOI
Aesthetically Design		5	
Comfort	The extent to which a potential customer's value, self-demand, precious experiment are matching with a particular system (Rogers, 1995)	5	DOI
Anxiety	Technology anxiety is a negative emotional response, and pertains to the fear or discomfort people experience when they think of using or actually use technology [71]. It also refers to the apprehension of an individual when he or she is faced with the possibility of using technology. Technology anxiety is derived from social cognitive theory [72]. (Deng 2013)	4	SCT
Perceived Value	this study refers to the perceived value of wearable devices as a potential customer's overall perception of wearable devices based on their beneðts and sacriðces (Yang et al. 2016)	3	
Habit	"the extent to which people tend to perform behaviors (use IS) automatically because of learning" (Limayem et al. 2007, p. 709).	3	UTAUT2

APPENDIX III.

All The Variables

Table 17.

	Nb item	Nb used	
Tool caracteristic			
Brand	2	3	Brand Name(1), Brand Familiarity(2)
Comfort	3	10	Comfortable(8), Acceptability(1), Wearability(1)
Esthetic	4	12	Aesthetically Design(9), Apearance evaluation(1), Appearance Orientation(1), Visual Attractiveness(1)
Function			
Information	1	1	Perceived Informativeness(1),
Mobile	3	7	Mobility(3), Ubiquity(3), Disturbance concern(1)
Openess	4	12	Compatibility(7), Communicability(3), Inter-operability(1), Personalization concern(1)
Playful	2	10	Enjoyment(8), Perceived Playfulness(2)
Reliability	9	21	System unreliability(2), Perceived Service quality(2), Perceived Content quality(1), Reliability(1), Replaceability(1), Technical Reliability(1), Perceived trustworthiness(3), Credibility of Information(1), Perception of Trust(9)
Performance	4	17	App Efficacy(1), Perceived Service Availability(1), Relative Advantage(3), Performance Expectancy(12)
Support	5	5	Support of Fitness(1), Support of Health(1), Support of Well-Being(1), Management support(1), Level of exercice encouragement(1)
Innovation	6	12	Personal Innovativeness(6), Observability of innovation(2), Information processing innovativeness(1), Product processing innovativeness(1), Rate Of Change of wearable(1), Novelty(1)
Value	2	15	Price Value(10), Perceived Value(5)
Security/Privacy	9	21	Perception of Privacy(9), Data Security(2), Perceived Privacy Invasion(2), Legislation Protection(1), Security(1), Sharing Personal Information(1), Transparency(1), Safety(3), Information Sensitivity(1)
Person			
Beliefs about tech	4	25	Attitude Toward Technology(22), Confirmation of belief(1), , Optimism level concerning the product(1), Beliefs toward tech(1),
Behavior	3	29	Behavioral intention(18), Exercice Behavior(2), Perceived behavioral control(9)
Self-Capability	11	20	Self-efficacy(7), Self Observation(2), Selective attention(1), Self-Care Agency(1), Self-Management(1), Self-Monitoring(1), Self regulation(1), Self-Reactance(1), Self Regulation(1), Self-Esteem(1), Self-actualization(3)
Ease to use	6	59	Ease of use(30), Facilitating Conditions(12), Effort Expectancy(11), Complexity(2), Relative advantage(2), Barrier to use(2)
Technophily	1	2	Ownership of ICT gadget(2)
Habit/Routine	3	8	Habit(4), Perceived routine constraints(3), cognitive inertia(1)
Health	7	9	Perceived Severity(2), Health Cognitive(2),Health Anxiety(1), Health Control belief(1), Health Stress(1), Hygienic Aspects(1), Skin Reactions(1)
Fitness	4	6	Perceived Physical Condition(3), Fitness Evaluation(1), Fitness Orientation(1), Physical Activity(1)
Knowledge	6	10	Technology Expertise(3), IT Knowledge(2), Medical Literacy(2), Need for Cognition(1), Prior Knowledge(1), Tech support and training(1)
Motivation	5	15	Hedonic Motivation(9), Self Expression Motivated(2), Intrinsic Motivation for Physical Activity(1), Level of Interest(1), Cue To Action(2)
Need	5	8	Physiological need(3), Love and Belonging(2),Need For Uniqueness(1), Need for Materialism(1), Gratification(1)
Psycho	10	11	Trialability(1), Perceived Sceptibility(1), Affective Quality(1), Perceived Burden(1), Perceived Vulnerability(1), Perceived Natural Border Crossing(1), Outcome Expectations(1), Neglect(2), Procrastination(1), Disregard(1)
Risk	4	7	Perceived Risks(3), Performance risk(1), Privacy Risk(2), Financial Risk(1)
Trait	11	19	Anxiete(4), Agreeableness(2), Conscientiousness(2), Extraversion(2), Neuroticism(2), Openness(2), Culture(1), Vanity(1), Expressiveness(1), Personal Initiative(1), Resistance to Change(1)
Usefulness	6	50	Perceived usefulness(41), System capability shortcomings(2), Functional Congruence(2), Usability(1), Perceived Benefit(3), App Satisfaction(1)
Social	13	46	Subjective norms(14), Social norm(12), Observational learning(3), Perceive Pressure(2), Social Image(2), External Influences(1), Interpersonal Influences(1), Perceived Prestige(1), Social Media Influence(1), Subcultural appeal(1), Usage of Social Media(1), Social Support(1), Visibility(3)

APPENDIX IV.

Different Aspects of Risk

Table 18.

Perceived Risk Facet	Description-Definition
Perceived Financial Risk	‘‘The potential monetary outlay associated with the initial purchase price as well as the subsequent maintenance cost of the product’’ (Grewal et al., 1994).
Perceived performance risk	‘‘The possibility of the product malfunctioning and not performing as it was designed and advertised and therefore failing to deliver the desired beneðts.’’ (Grewal et al., 1994) “This dimension of perceived risk is similar to the usefulness or functionality of products”.(Lim, 2003)
Perceived social risk	“Potential loss of status in one’s social group as a result of adopting a product or service, looking foolish or untrendy” (Featherman & Pavlou, 2003)
Perceived physical risk	“is the possibility that products are harmful to individuals’ health or products do not look as good as the individuals expect” (Lim, 2003)
Perceived psychological risk	“The risk that the selection or performance of the producer will have a negative effect on the consumer’s peace of mind or self-perception (Mitchell, 1992). Potential loss of self-esteem (ego loss) from the frustration of not achieving a buying goal.”(Featherman & Pavlou, 2003) “ In addition to shopping time, this dimension includes waiting time for receipt of products as well as time spent on returning unsatisfactory products” (Lim, 2003)
Perceived time-loss risk	“Consumers may lose time when making a bad purchasing decision by wasting time researching and making the purchase, learning how to use a product or service only to have to replace it if it does not perform to expectations.”(Featherman & Pavlou, 2003) “In addition to shopping time, this dimension includes waiting time for receipt of products as well as time spent on returning unsatisfactory products” (Lim, 2003)
Perceived personal risk	“is the possibility that individuals may be harmed because of their purchase behavior. For example, they are likely to suffer if their credit cards information is stolen.” (Lim, 2003)
Perceived privacy risk	“Potential loss of control over personal information, such as when information about you is used without your knowledge or permission. The extreme case is where a consumer is ‘‘spoofed’’ meaning a criminal uses their identity to perform fraudulent transactions.” (Featherman & Pavlou, 2003) “This dimension of risk includes undisclosed capture of information like consumers’ shopping habits.” (Lim, 2003)
Quality risk	“The possibility of the product malfunctioning and not performing as it was designed and advertised and therefore failing to deliver the desired benefits” (Zhang et al., 2012)
Health risk	“Potential loss of health because of prolonged use of computer will cause fatigue or visually impaired, pressure on one’s heart, or buying counterfeit products which is harmful to one’s health” (Zhang et al., 2012)
Economic risk	“The potential monetary outlay associated with the initial purchase price as well as the subsequent maintenance cost of the product, and the potential financial loss due to fraud” (Zhang et al., 2012)
Overall risk	“A general measure of perceived risk when all criteria are evaluated together.” (Featherman & Pavlou, 2003)

APPENDIX V.

The Concept of Risk in IS Research

Table 19.

Authors	Technology	Theory	Risk Type
McLeod, Pippin, & Catania (2009)	Tax software	UTAUT	Perceived Risk
(Cocosila et al., 2009)	New technology	Motivation theory	Finance, Social, Privacy, Psychology
Lian & Yen (2014)	Online shopping	Innovation resistance theory and UTAUT	Risk barrier
Schaupp, Carter, & McBride (2010)	E-file Taxe	UTAUT	Perceived Risk
(Horst et al., 2007)	E-government services	TPB	Risk Perception
Miltgen, Popovic, & Oliveira (2013)	Biometrics	TAM, DOI, UTAUT	Perceived Risk
(Ayanso et al., 2015)	Electronic Medical Record	Expectation-Confirmation Theory	Performance, Finance, Time, Psychological, Social, Privacy, Overall
(Kim et al., 2008)	E-commerce	Valence Framework	Perceived Risk
(Lee, 2009)	Online trading	TAM, TPB, Rational Choice	Perceived Risk
(Nicolaou & McKnight, 2006)	Quality Data Exchange	Risk Theory, IS Success Model	Perceived Risk
(Yang et al., 2016)	Website	TRA	Finance, performance, psychological, social risk
(Dinev et al., 2006)	e-commerce	Privacy calculus	Perceived Risk
(Verhagen et al., 2006)	e-commerce	TRA	Intermediary and seller risk
(Lu et al., 2005)	Online applications	TAM	Physical, Functional, Social, Time-loss, Financial, Opportunity cost, Information
(Anderson & Agarwal, 2011)	Disclose Personal Health information	Privacy calculus and Risk as feelings	Risk as feeling
(Featherman & Pavlou, 2003)	e-service	Perceived Risk Theory, TAM	Performance, Financial, Time, Psychological, Social, Privacy, Overall
Martins, Oliveira, & Popovic (2014)	Internet Banking	UTAUT	Performance, Finance, Time, Psychological, Social, Privacy, Overall
(Aytes & Connolly, 2004)	Computer security	Rational Choice theory	Probability of negative consequences
(Huigang Liang et al., 2017)	Online Health Information	Rational Choice Theory, IS Success Model	Perceived Risk
(Hong & L. Thong, 2013)	Internet Privacy Concern	Not Applicable (Literature review)	Risk Belief
(Bulgurcu et al., 2010)	Computer security	Rational Choice theory, TPB	Benefit-Cost of Compliance
(Li & Huang, 2009)	Online shopping	TAM	Performance, Finance, Time, Psychological, Social, Privacy, Overall

APPENDIX VI.

The Survey

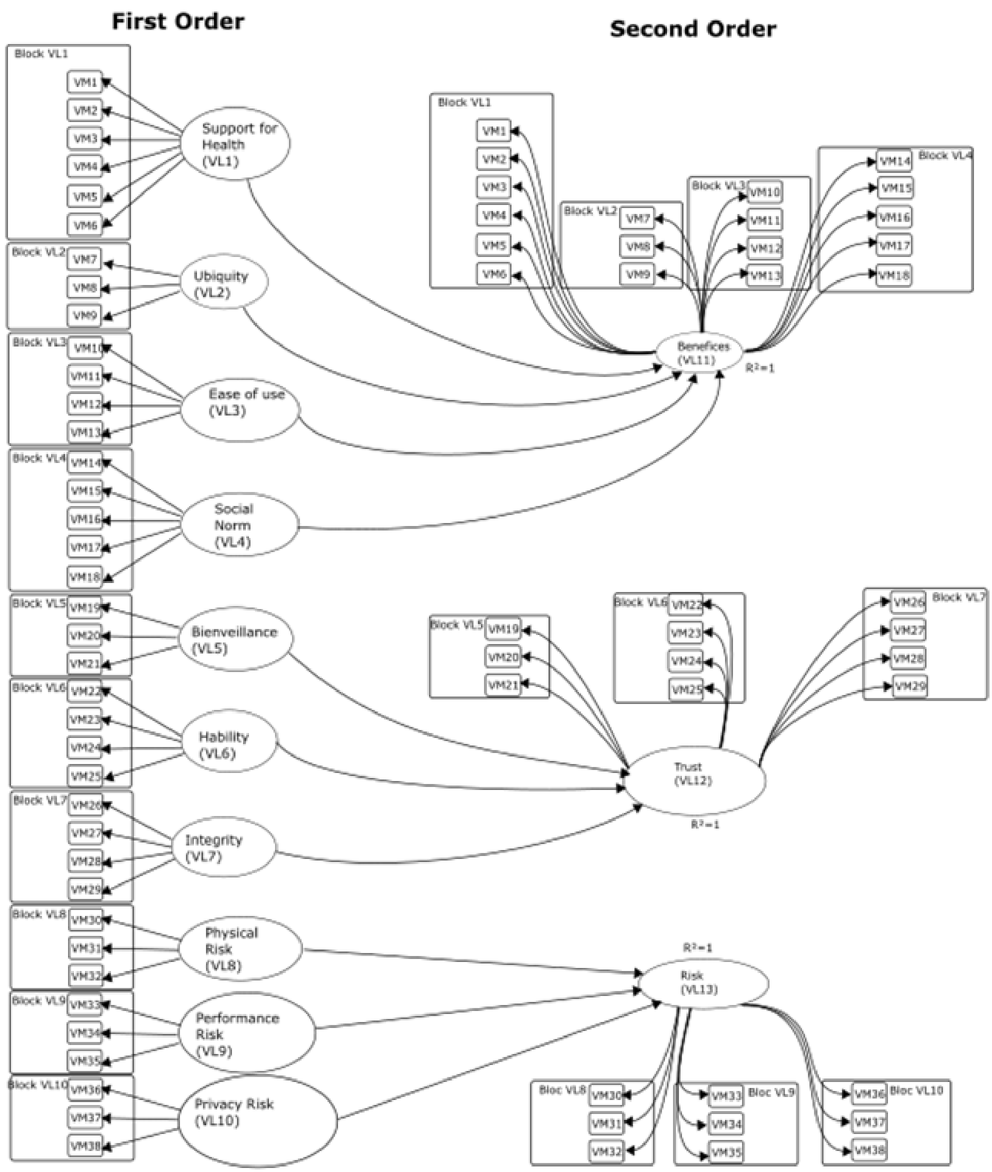
Table 20.

Concept	The survey
Ease of Use	
Modified 4-element scale based on (Pfeiffer et al., 2016) on Venkatesh et al. (2003), Lu et al. (2005) and Gefen et al. (2003).	EOU1 The handling of a self-monitoring device is simple and easy for me to understand.. EOU2 The use of self-monitoring devices does not require high demands on the user. EOU3 Learning how to operate a self-tracking device is easy. EOU4 The handling of self-monitoring devices is not complicated.
Ubiquity	
Three-item mobility scale from Hirose and Tabe (2016) based on Okazaki et al, (2013).	UB1 The self-tracking devices are handy because I can use them without difficulty wherever I am. UB2 The use of self-tracking tools outside of my home or workplace is not a problem for me. UB3 I find convenient to use these tools because they do not make me dependent on any fixed installation.
Support to Health	
Modified 5-element scale based on (Pfeiffer et al., 2016)	SH1 Using a self tracking device increases my health awareness. SH2 The self-tracking devices allow me to take care of my body. SH3 Self-monitoring devices can help me prevent illness. SH4 Using a self tracking device increases my sense of responsibility for my own body. SH5 The use of a self-monitoring device facilitates a healthier life. SH6 The use of a self tracking device contributes to the knowledge of my body (auto-construit)
Social Norms	
Modified 5-element scale based on Pfeiffer et al (2016) based on Venkatesh et al (2012)	SN1 People I value the opinions recommend the use of a self-tracking device. SN2 I have the pleasure of comparing myself to friends / acquaintances / strangers using self-tracking devices. SN3 The use of self-tracking devices would be positively noticed by the people I know. SN4 People who are important to me think I should use a self-tracking device. SN5 The self-tracking devices give me the opportunity to communicate with people who share the same ideas.
Trust-Benevolence	
Modified 4-element scale according to Mou & Cohen, (2014)	TB1 I expect the self-tracking tool supplier to have good intentions for me. (Hwang et Lee 2012). TB2 I expect the self-tracking tool supplier to act in my best interest. (Thatcher et al., 2013). TB3 I expect the self-tracking tool supplier to be well-intentioned. (Hwang et Lee 2012).
Trust-Integrity	
Modified 4-element scale according to Mou & Cohen, (2014)	TI1 The self-tracking tool supplier is honest in his dealings with me. (Thatcher et al., 2013). TI2 I would characterize the self-tracking tool supplier as honest. (Thatcher et al., 2013). TI3 The supplier of self-tracking tools would meet its commitment to provide quality data. (Thatcher et al., 2013). TI4 The supplier of self-tracking tools is sincere and genuine. (Thatcher et al., 2013).
Trust-Ability	
Modified 4-element scale according to Mou & Cohen, (2014)	TA1 I believe that the self-tracking tool provider is effective in helping me keep track of my health data. TA2 The provider of self-monitoring tools fulfils its health monitoring role very well. (Thatcher et al., 2013). TA3 Overall, the provider of self-monitoring tools is capable and competent in health monitoring. (Thatcher et al., 2013). TA4 In general, the provider of self-monitoring tools is very knowledgeable in health monitoring. (Thatcher et al., 2013).
Physical Risk	
Modified 3-element scale based on (Gurtner, 2014) from Mieres, Martín, and Gutiérrez (2006)	PHR1 I'm afraid the self-tracking devices aren't safe for me. PHR2 I'm afraid that the self-tracking devices may be damaging to my health. PHR3 I think the self-tracking devices can cause me physical damage.
Performance Risk	
Modified 3-element scale based on (Yang et al., 2016) after Gewal et al. (1994) and Stone and Grønhaug (1993).	PER1 I am concerned that the self-tracking devices will not provide the level of benefits I expect. PER2 It is not certain that the self-tracking devices will function satisfactorily. PER3 It is not certain that the self-tracking devices will perform the functions described in the advertisement.
Private Risk	
Modified 3-element scale based on (Li et al., 2016)	PR1 it would be risky to disclose my personal health information to providers of self-tracking tools. PR2 disclosure of my personal health information to providers of self-tracking tools could result in significant losses. PR3 there would be too much uncertainty associated with disclosing my personal health information to providers of self-tracking tools.
Intention to use	
Modified 4-element scale according to Pfeiffer et al (2016) based on Venkatesh (2012)	BI1 With a high probability, I will use a self-tracking device in the future. BI2 If I get a chance, I'll use a self-tracking device. BI3 I intend to purchase a self-tracking device in the future. BI4 I will recommend others to use a self-tracking device as well.

APPENDIX VII.

First Step in The Construction of a Second Order Model

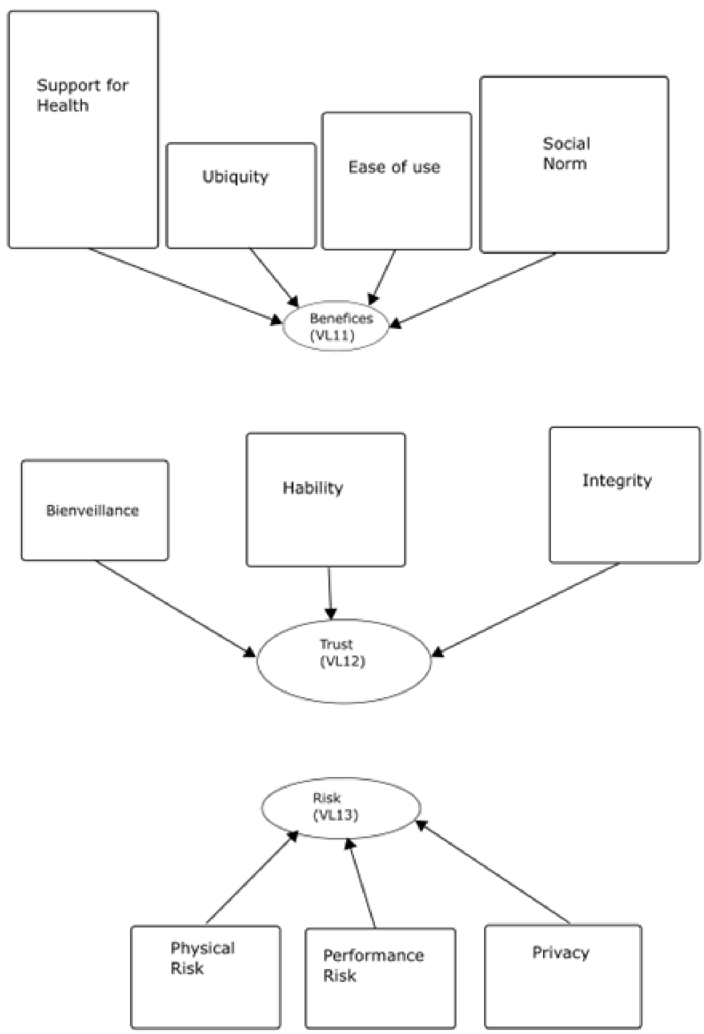
Figure 5.



APPENDIX VIII.

Second Step In The Construction of A Second Order Model

Figure 6.



APPENDIX IX.

Internal Validity

Table 21.

Item	Loading	Mean	Standard Deviation (STDEV)	T Statistics	rho_A	Composite Reliability	Average Variance Extracted (AVE)
BI1	0.955	0.955	0.007	137.368	0.931	0.951	0.867
BI2	0.898	0.897	0.022	41.579			
BI3	0.939	0.939	0.009	104.370			
TA1	0.798	0.799	0.030	26.900	0.835	0.889	0.668
TA2	0.820	0.818	0.036	22.925			
TA3	0.833	0.832	0.030	27.540			
TA4	0.817	0.817	0.028	28.991			
TB1	0.914	0.914	0.015	61.604	0.918	0.947	0.857
TB2	0.947	0.947	0.008	112.258			
TB3	0.917	0.916	0.016	56.061			
TI1	0.782	0.779	0.040	19.659	0.874	0.913	0.725
TI2	0.888	0.887	0.020	44.225			
TI3	0.855	0.855	0.023	37.998			
TI4	0.876	0.875	0.027	31.954			
EOU1	0.857	0.859	0.0.24	35.842	0.867	0.906	0.707
EOU2	0.790	0.785	0.050	15.734			
EOU3	0.884	0.880	0.027	32.280			
EOU4	0.884	0.885	0.027	33.089			
SN1	0.788	0.794	0.028	28.046	0.840	0.867	0.567
SN2	0.719	0.713	0.053	13.499			
SN3	0.805	0.803	0.036	22.260			
SN4	0.712	0.706	0.051	14.000			
SN5	0.737	0.731	0.050	14.682			
PHR1	0.777	0.776	0.037	20.957	0.817	0.891	0.732
PHR2	0.902	0.903	0.012	75.994			
PHR3	0.882	0.881	0.024	36.568			
PER1	0.799	0.797	0.041	19.535	0.611	0.776	0.539
PER2	0.598	0.582	0.115	5.193			
PER3	0.789	0.791	0.041	19.443			
PR1	0.890	0.888	0.018	48.234	0.905	0.940	0.839
PR2	0.937	0.936	0.010	91.278			
PR3	0.921	0.921	0.014	67.094			

continued on next page

Table 21. Continued

Item	Loading	Mean	Standard Deviation (STDEV)	T Statistics	rho_A	Composite Reliability	Average Variance Extracted (AVE)
SH1	0.795	0.795	0.032	24.873	0.893	0.914	0.639
SH2	0.845	0.844	0.022	38.675			
SH3	0.693	0.689	0.050	13.780			
SH4	0.884	0.883	0.017	53.377			
SH5	0.825	0.823	0.027	30.863			
SH6	0.740	0.736	0.039	19.162			
UB1	0.866	0.865	0.026	33.184	0.784	0.874	0.699
UB2	0.886	0.886	0.021	41.695			
UB3	0.750	0.751	0.043	17.530			
Information on the constructs BI: Behavior Intention							
TA: Trust Ability							
TB: Trust Benevolence							
TI: Trust Integrity							
EOU: Ease Of Use							
SN: Social Norms							
PHR: Physical Risk							
PER: Performance Risk							
Private Risk							
SH: Support To Health							
UB: Ubiquity							

APPENDIX X.

Discriminant Validity

Table 22.

	Behaviour Intentio	Trust Ability	Trust Benevolence	Trust Integrity	Ease Of Use	Social Norms	Physical Risks	Performance Risks	Private Risks	Support To Health	Ubiquity
BI1	0,955	0,317	0,055	0,225	0,176	0,333	-0,207	-0,053	-0,235	0,376	0,319
BI2	0,900	0,304	0,066	0,197	0,132	0,413	-0,064	0,079	-0,115	0,430	0,233
BI3	0,938	0,288	0,009	0,213	0,191	0,328	-0,186	-0,070	-0,224	0,382	0,336
TA1	0,275	0,798	0,383	0,557	0,259	0,302	-0,134	0,108	-0,020	0,433	0,302
TA2	0,247	0,820	0,381	0,521	0,154	0,335	-0,090	0,112	-0,044	0,462	0,218
TA3	0,342	0,834	0,370	0,625	0,191	0,390	-0,089	-0,010	-0,037	0,435	0,377
TA4	0,194	0,817	0,315	0,567	0,214	0,290	-0,118	0,052	0,013	0,286	0,181
TB1	-0,007	0,413	0,914	0,563	0,166	0,226	-0,048	0,115	0,046	0,372	0,178
TB2	0,062	0,432	0,947	0,607	0,148	0,296	-0,024	0,139	0,101	0,355	0,254
TB3	0,071	0,387	0,917	0,597	0,141	0,298	0,009	0,120	0,066	0,272	0,185
TI1	0,109	0,472	0,691	0,781	0,199	0,367	-0,041	-0,036	-0,051	0,268	0,182
TI2	0,224	0,582	0,497	0,889	0,278	0,374	-0,079	-0,073	-0,095	0,289	0,305
TI3	0,211	0,688	0,477	0,856	0,229	0,368	-0,068	-0,021	-0,009	0,310	0,283
TI4	0,227	0,619	0,511	0,876	0,187	0,353	-0,094	-0,065	-0,111	0,348	0,270
EOU1	0,169	0,221	0,130	0,210	0,857	0,055	-0,118	-0,033	-0,069	0,155	0,522
EOU2	0,118	0,171	0,178	0,165	0,749	0,056	-0,135	0,085	0,012	0,190	0,351
EOU3	0,113	0,203	0,119	0,284	0,865	0,019	-0,155	0,026	-0,074	0,100	0,536
EOU4	0,196	0,240	0,127	0,226	0,886	0,043	-0,095	0,029	-0,135	0,171	0,610
SN1	0,344	0,518	0,291	0,431	0,128	0,778	0,047	0,089	0,066	0,507	0,180
SN2	0,246	0,162	0,151	0,258	-0,051	0,726	0,281	0,178	0,074	0,223	0,119
SN3	0,256	0,347	0,315	0,407	0,068	0,800	0,047	0,064	0,090	0,321	0,177
SN4	0,307	0,195	0,143	0,214	0,010	0,713	0,182	0,072	0,099	0,264	0,081
SN5	0,272	0,188	0,164	0,243	-0,013	0,753	0,261	0,093	0,150	0,293	0,045
PHR1	-0,089	-0,059	0,059	-0,015	-0,052	0,129	0,776	0,294	0,347	0,144	-0,005
PHR2	-0,206	-0,135	-0,041	-0,114	-0,087	0,160	0,903	0,220	0,357	-0,028	-0,152
PHR3	-0,130	-0,142	-0,076	-0,081	-0,242	0,212	0,883	0,188	0,312	-0,007	-0,226
PHRE1	-0,039	0,088	0,146	-0,047	0,071	0,088	0,186	0,802	0,359	0,060	0,066
PHRE2	0,041	0,232	0,194	0,162	0,054	0,188	0,096	0,590	0,162	0,246	0,185
PHRE3	-0,021	-0,070	0,003	-0,157	-0,044	0,049	0,287	0,790	0,283	0,049	-0,119
PR1	-0,169	-0,058	0,014	-0,089	-0,104	0,119	0,394	0,316	0,890	-0,017	-0,133
PR2	-0,174	0,019	0,122	-0,043	-0,054	0,160	0,360	0,370	0,937	0,087	-0,067
PR3	-0,231	-0,038	0,076	-0,084	-0,070	0,060	0,337	0,359	0,921	0,083	-0,114
SH1	0,314	0,391	0,284	0,253	0,155	0,297	-0,044	0,089	0,058	0,795	0,258
SH2	0,398	0,376	0,299	0,338	0,185	0,369	-0,056	0,030	0,002	0,845	0,324
SH3	0,189	0,381	0,261	0,301	0,043	0,337	0,173	0,086	0,171	0,693	0,098
SH4	0,313	0,361	0,271	0,226	0,165	0,358	0,044	0,163	0,099	0,884	0,278
SH5	0,386	0,415	0,268	0,303	0,179	0,394	0,058	0,102	-0,032	0,824	0,341
SH6	0,407	0,467	0,349	0,302	0,130	0,393	0,051	0,152	0,001	0,740	0,226
UB1	0,287	0,307	0,133	0,288	0,574	0,144	-0,118	-0,022	-0,104	0,263	0,866
UB2	0,287	0,270	0,166	0,254	0,577	0,095	-0,098	-0,006	-0,141	0,244	0,886
UB3	0,226	0,253	0,264	0,224	0,360	0,184	-0,162	0,104	-0,038	0,313	0,750

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