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THÈSE

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The connected consumer: A theoretical framework of consumer adoption/consequences of the Internet of Things and smart connected objects

Discipline : **Sciences de Gestion**

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The attraction to a product or service is an amalgam of rational and emotional factors. Emotions play a part in every purchase decision but... very few purchases are entirely emotional (MacKay, 1999)

The Internet of Things has the potential to change the world, just as the Internet did. Maybe even more so (Ashton, 2009)

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GENERAL INTRODUCTION

Over the last decade, technological and Internet innovations have increasingly invaded the consumer market (N’Goala, 2016). 50 to 100 billion smart connected objects (SCO) are expected by 2020, which represents almost seven SCO per person (Cisco, 2017). The ‘Internet of PCs’ of the 90s has become an integrated ‘Internet of Things’ (IoT) (Popescul & Georgescu, 2013). Every object can become ‘connected’, with basic sensors, or ‘smart’, using in addition artificial intelligence. Figure 1 shows the evolution of the Internet and IoT over time to set the context of this thesis.

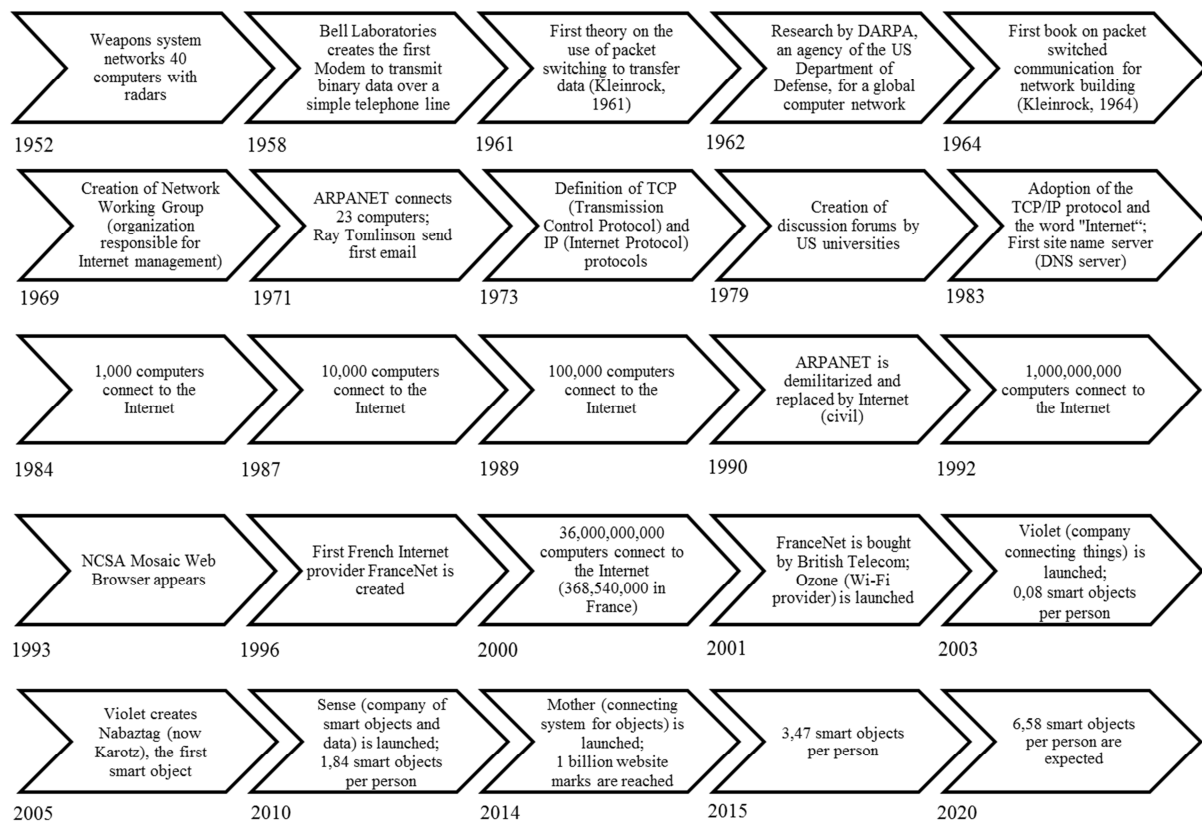


Figure 1: Evolution of the Internet and IoT over time

The use of the Internet evolves with innovations, and with changing consumer behaviors and demand. If the word Internet is first used in 1983, the term of IoT comes from Kevin Ashton in 1999, with the context of supply chain management: “we waste water, electricity, rubbish; there are thousands of things we can generally make better and improve our quality of life” (Ashton, 1999). Ashton then defined the IoT as “the development of the Internet” (Ashton, 2009). Regarding the strengths of the IoT, there is first a large offer from many manufacturers. Startups such as Violet or Sense were the first manufacturers to enter the IoT

segment with SCO, and then major international companies invested into the IoT as well, such as Google, Amazon, Microsoft, or Samsung, consolidating the ecosystem of supply and demand. Secondly, networks are mature, with effective Bluetooth, Wi-Fi, or 4G networks (5G networks by the beginning of 2020). For example, smart bracelets, smart watches or smart clothes can measure sport performances, smart mattresses or smart pillows can measure sleep quality, or smart airplane production lines can anticipate technical issues. Third, interoperability between SCO is an asset. According to B.K. Yoon (2009), Samsung CEO, 90% of our things can connect to the Internet no matter the product or brand. Fourth, artificial intelligence attracts more and more consumers, allowing them to ensure an innovative and attractive environment. These innovations should transform the way people live and improve their quality of life (Porter & Heppelmann, 2014). SCO guide users to reach desired goals, such as sleep monitoring, sport activity or other health measures, thereby changing consumer behaviors and ways of living (Yang et al., 2013). Further, the success of the IoT is vital for companies, which invested \$6 trillion into IoT solutions in 2016, expecting a \$13 trillion return over investment by 2025 (Business Insider, 2016). Thus, the IoT is a powerful driving factor for networking and communication in both industrial and academic research (Xu et al., 2010). This 'new' technology, that is becoming a common platform, disrupts relationships between consumers and companies (Bohli et al., 2009); in essence, this is a timely research.

However, there are also barriers to the IoT acceptance and development in France. Innovations can fail due to changing demand, user reluctance, strong competition, or health and dependence fears. For example, 80% of French people perceive SCO as useless gadgets (Opinion Way, 2017). Companies need to demonstrate the benefit of their products and services. Besides, the IoT brings out privacy invasion and data management issues: users cannot always manage the data whereas it can be registered in external databases. Thereby, ethical problems arise because of the ubiquity and omnipresence of the IoT (e.g., consumers forget the technology presence due to the small sizes of sensors and their habit of using SCO), and its autonomous and unpredictable characteristics (e.g., the data is automatically collected and this information flow is hard to control) (Van der Hoven, 2013). Tangible and intangible dimensions should be taken into account (Benamar et al., 2019). Users' ability to control the IoT can be very low, especially with intangible IoT environments, whereas research showed that the acceptance of SCO is favored with technology trust (Hoffman et al., 1999). The anonymization of the data and security of SCO and networks remain some very important challenges for companies to overcome (Dimitriadis & Kyrezis, 2010).

RESEARCH OBJECTIVES AND CONTRIBUTIONS

As research on the IoT and smart technologies in marketing is scarce (Verhoef et al., 2017), this thesis has theoretical, methodological, and managerial objectives, as well as expected contributions that are explained in the following paragraphs.

A. Theoretical objectives and contributions

First, as clear definitions are missing or confusing in the literature, in chapter 1, we define and classify the IoT and its associated smart technologies (i.e., smart/connected objects, smart/connected apps, and smart environments), which is also one of the main contributions of this doctoral work. This goal responds to a call for research from Verhoef et al. (2017). To do this, we conduct a literature review using 134 articles on the IoT and smart technologies, with 14 of them from marketing literature.

In chapter 2, a discussion of different studies highlights the relevant antecedents of the acceptance of the IoT and smart technologies. In section 2.1., an exploratory qualitative analysis is conducted to highlight relevant antecedents of acceptance of the IoT and smart technologies. According to several research calls on the topic, an extremely important research priority is to explain the antecedents that lead to the acceptance or rejection of IoT and smart technologies (Foroudi et al., 2018; Oh et al., 2007; Verhoef et al., 2017). This first study—entitled “*An exploratory qualitative analysis of the IoT technology acceptance: The roles of technology and self-improvement benefits, perceived risks, and user personalities*”—deals with the acceptance or rejection of the IoT and smart technologies as well as perceptions of SCO, smart apps, and smart environments (*targeted journal: Journal of Marketing Management*). Thus, this qualitative research builds on prior research: the acceptance and use of the IoT are both aspects that are influenced by utility benefits from the TAM (Davis, 1989) (e.g., functional characteristics with usefulness and ease of use) as well as by new variables, such as self-improvement benefits (e.g., well-being, social image and status), perceived risks and fears (e.g., privacy concerns, health fears with radiations and addiction consequences), and personality traits (e.g., innovativeness, well-being and empowered personalities). Thereafter, we create a classification of the IoT and smart technologies in order to fill the gap in marketing literature.

Second, chapter 2 contributes to the literature by conceptualizing the qualitative results with several quantitative studies. The goal remains to better understand the antecedents that influence the acceptance of IoT and smart technologies as well as their usage. To do this, we develop an extended TAM that measures traditional TAM variables, such as perceived usefulness, perceived ease of use, intention to use, and actual use (Davis, 1989); this TAM includes new and rarely investigated concepts, such as perceived well-being, perceived social image, privacy concerns, and user characteristics on adoption intentions (King & He, 2006; Venkatesh et al., 2003). For each construct, we attempt to improve internal (i.e., use reliable and valid measurements to measure specific constructs) and external validity (i.e., different samples, and different IoT technologies). We simultaneously test if the TAM is still relevant and applicable to the IoT and smart technologies context, as the TAM is often considered insufficient to explain other antecedents of technology adoption (Benbasat & Barki, 2007; Chuttur, 2009).

The first quantitative study we present in section 2.2. (*targeted journal: Journal of Business Research*) has been presented at the EMAC 2016 and AFM 2016 under the title “A theoretical model incorporating social influence and cognitive processes to explain the adoption of the Internet of Things and smart connected objects”. Thereafter, it was improved upon with another data set and published at the EMAC 2017 under the title “The impact of consumer well-being and trust on the Internet of Things adoption and word-of-mouth intentions”. A theoretical model is built upon our previous qualitative study and theory. Three sets of samples comprising non-users, innovators, early majority, and late majority of users are surveyed during three years. The main TAM variables (e.g., perceived usefulness, perceived ease of use, intention to use, real use) are relevant to SCO in accordance with the adoption stage. Utility benefits (e.g., perceived usefulness, ease of use) are the main reasons leading to acceptance, whereas well-being and social recognition are the main motives to re-use SCO. Further, privacy concerns are the main barriers to adoption. Consumer decisions involve risk since consequences cannot be anticipated with certainty (Bauer, 1960). However, these concerns decrease when consumers perceive higher utility, well-being, and social benefits or when they rate a higher level of innovativeness than others. Thus, we confirm that the TAM is a robust model with strong psychometric properties (King & He, 2006; Lederer et al., 2000; Legris et al., 2003) and its scales are valid and reliable (Hendrickson et al., 1993). Thus, this study contributes to the literature with an extended TAM, adapted to the context of SCO, with new antecedents such as perceived well-being, perceived social image, privacy concerns, and

innovativeness. We also show that there are significant differences in accordance with experience of use, thereby highlighting theoretical and managerial insights.

In section 2.3., we present our second quantitative study entitled “*A longitudinal study to explain the adoption of sleep apps with the TAM, perceived well-being, quantified self, privacy concerns and different types of personalities*” (targeted journal: *Technological Forecasting and Social Change*). This longitudinal study explains the adoption of sleep apps with the TAM, perceived well-being, quantified-self, privacy concerns, and different types of personalities. Therefore, an extended TAM is built upon theory to study the acceptance before use and then after using a sleep app for one week. The main variables of the TAM (e.g., perceived usefulness, perceived ease of use, intention to use, real use) are relevant in the adoption process of a sleep app, along with other variables such as perceived well-being, quantified self, privacy concerns, and personalities (e.g., high versus low well-being and high versus low empowered personalities). Therefore, the main contribution of this study is to understand the adoption process of a smart technology, as suggested by Verhoef et al. (2017). Further, we show the relevance of the TAM with a new context of study (Wu & Lu, 2013). Third, research has shown that users might change their technology usage and beliefs over time (Ashraf et al., 2014; Gilly et al., 2012; Rogers, 2003) so we show the role of new antecedents over time.

Then, section 2.4. aims to study if there are differences in consumer perceptions according to IoT contexts and personalities. To do this, we define and measure different types of IoT users, as the TAM shows differences in technology perceptions according to user personalities (Davis, 1989). We present two studies: in section 2.4.1., the first one entitled “*The acceptance process of the Internet of Things: How to improve the acceptance of the IoT technology?*” is a book chapter published in “*Smart Marketing with the Internet of Things*” (2018; Simões, D., Barbosa, B., & Filipe, S. (Eds.), 300p). In section 2.4.1., the second study, “*Consumers’ acceptance and resistance factors toward smart connected stores*”, is a book chapter for “*Anthropological Approaches to Understanding Consumption Patterns and Consumer Behavior*” (full chapter under minor revisions, final version submitted in December 2019) for the literature and managerial recommendations, and targeted journal for the data and results is *Technological Forecasting & Social Change* journal. For both studies, theoretical models are built upon theory. With regard to the methodology, a short video on a smart home or a smart store is presented to our respondents before they answer the survey questions. The results

reveal that the acceptance of smart environments is influenced by privacy concerns, utility value, perceived well-being, and social image. Innovative, well-being, or empowered personalities influence the acceptance process. Therefore, the main contribution of these two studies is to understand and describe the acceptance process of smart environments (Verhoef et al., 2017). Moreover, our typology of users should help companies to refine targeting strategies.

Fourth, once consumers adopt and start to use IoT and smart technologies, the consequences of these technologies on their feelings and perceptions remain unclear (Atzori et al., 2010). More precisely, we contribute to this literature gap by investigating, in chapter 3, if the IoT and smart technologies improve or worsen perceived well-being (Atzori et al., 2010) over time (Etkin, 2016). Simultaneously, we deepen the concept of perceived well-being in the context of the IoT and smart technologies. Indeed, consumer well-being is increasingly attracting the interest of researchers in marketing (Anderson et al., 2013; Arora et al., 2017; Kim et al., 2016; Krebs & Duncan, 2015). Moreover, the relationship between perceived well-being and the acceptance of IoT and smart technologies is not clear (Steptoe et al., 2012). This direction is not necessarily intuitive, as perceived well-being can influence the intentions to adopt new technologies (Andreasen et al., 2012; Curran & Meuter, 2007; Dabholkar & Bagozzi, 2002; Davis & Pechmann, 2013), as we demonstrate in chapter 2. Further, using new technologies can improve (Atzori et al., 2010; Etzioni, 1999; Harkin et al., 2016; Kluger & DeNisi, 1996; Porter & Heppelmann, 2014; Xia et al., 2012) or worsen (Etkin, 2016) perceived well-being over time, as we study in chapter 3. Therefore, we further investigate knowledge on the concept and measurement of perceived well-being in the context of technology adoption (Steptoe et al., 2012). For this, two studies are conducted. The first is a quantitative study on user experience of SCO. Thus, in section 3.1., we present the second part of Article 2, entitled “*How do smart connected objects improve consumer well-being over time? (targeted journal: Journal of Business Research)*”. In this study, a theoretical model is built; non-users, early adopters, the early majority, and the late majority of users are surveyed during three years. We show that the main TAM variables (e.g., perceived usefulness, perceived ease of use, intention to use, real use) influence perceived well-being. Moreover, perceived social image gives users more positive feelings regarding their experience of use. We also show that experience of use decreases privacy concerns and increases innovativeness, thereby improving perceived well-being.

Then, in section 3.2., we present the second part of Article 3, entitled “*Do digital applications improve users' feelings of well-being?*” (targeted journal: *Technological Forecasting and Social Change*) published at the EMAC and AFM conferences 2018. For this study, a theoretical model is built and respondents test a sleep app for one week. Perceived ease of use, perceived usefulness, intention to use, and real use are found to influence feelings of well-being. Even though privacy concerns are one of the main obstacles of using sleep apps, they do not significantly decrease perceived well-being. Other factors linked to personality traits moderate the theoretical model. This research contributes to understanding how well-being is influenced by the use of a smart app. We also contribute to the literature on consumer well-being by measuring the concept of well-being and defining directions of the influences between the variables. With this study, we intend to respond to calls for research on consumer well-being (Anderson et al., 2013; Munzel et al., 2018; Wunderlich et al., 2013).

B. Methodological objectives and contributions

From a methodological perspective, the first contribution of this research is to develop and adapt scales to measure perceived well-being and personalities (i.e., well-being and empowered personalities) in the context of the IoT and smart technologies, which is presented in chapters 2 and 3.

The second methodological contribution is that we conduct a longitudinal study on smart apps (in articles 3 and 7) measured at two different times—before and after usage. This methodology improves the understanding of adoption through time and experience of use, as the literature has shown differences in perceptions according to the stage of adoption (Rogers, 2003; Etkin, 2016).

The third methodological contribution is to combine both qualitative and quantitative studies to respond to our research problem. First, the qualitative studies indicate the relevant antecedents of the adoption of IoT and smart technologies from the literature in order to better orientate and focus on quantitative studies. The subsequent quantitative studies measure these antecedents in order to deepen the research on specific concepts—such as perceived well-being, perceived social image, privacy concerns, and types of personalities—and to build theoretical models on the acceptance and usage of IoT and smart technologies and their consequences on perceived well-being.

C. Managerial objectives and contributions

This research highlights the key factors of the adoption of IoT and its components along with consumers' motivations and obstacles. This would enable managers to better choose actions with regard to communication and targeting strategies, as well as the development of products and services (e.g., Balagué & Lee, 2007). More precisely, chapter 2 provides recommendations regarding privacy concerns and benefits to target non-users or early adopters, including perceived well-being, to favor loyalty of use.

The second managerial contribution is the focus on perceived well-being, which is either rarely used, or not used at all, by managers. In chapter 3, we focus on the antecedents of perceived well-being so that managers ascertain how to improve positive feelings using the IoT and smart technologies.

The third managerial contribution of this research is the definition and measurement of types of IoT consumers according to personalities (i.e., well-being and empowered personalities), which is discussed in chapters 2 and 3. Through such a discussion, managers can define the majority of their users, or target groups, and thus, refine personalized communication strategies.

LITERATURE REVIEW

The literature review was done thanks to a systematic review process. Firstly, we decided the inclusion criteria (i.e., IoT, smart objects, connected objects, smart apps...) and secondly, we selected the database (i.e., Business Source Complete) to find articles linked to the topic (Eden et al., 2011). Two main research topics are related to the IoT in marketing research. The first one is related to the reasons for the acceptance and rejection of the IoT and smart technologies, since the literature has not provided any significant results yet (Verhoef et al., 2017). The second one is related to the influence of these two aspects on consumer behavior and perceived well-being (Porter & Heppelmann, 2014). In the literature, 134 papers have been published on the IoT in peer-and-review journals since 2002 in various fields such as sciences, finance, engineering, management, economics, law, business, and consumer research, according to Business Source Complete database. Figure 2 presents the number of publications on the IoT and related issues (i.e., smart objects, connected objects, smart apps, and mobile apps) during the previous two decades in all disciplines.

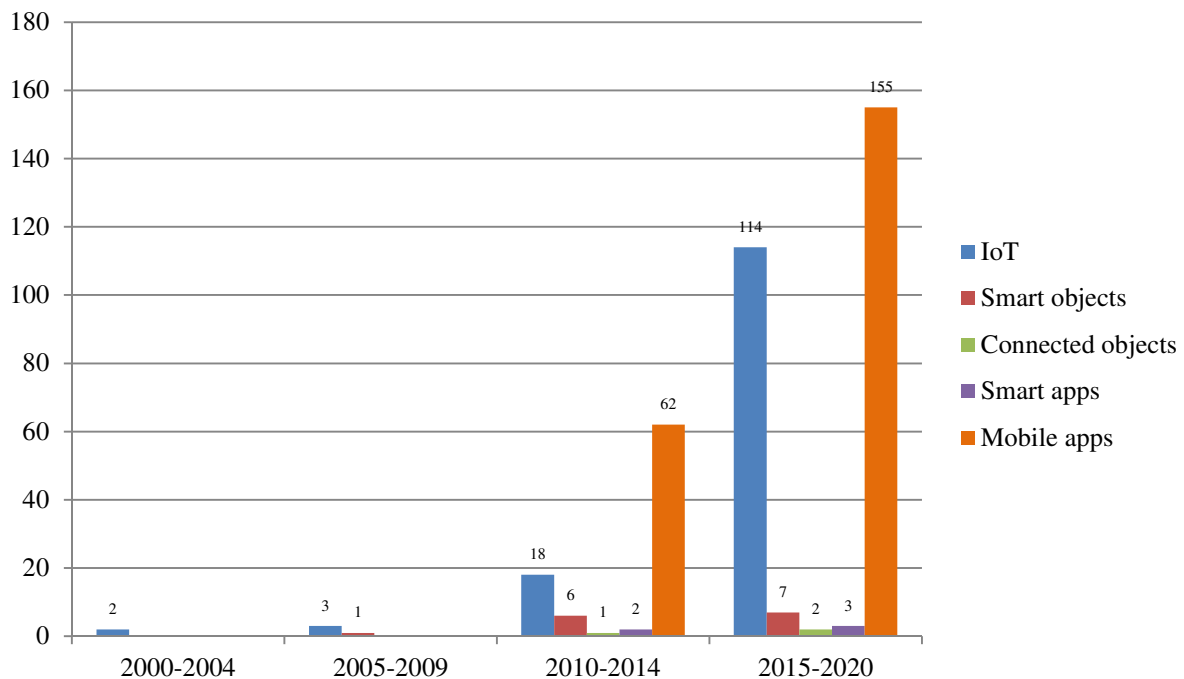


Figure 2: The number of publications on the IoT in all disciplines

As depicted in Figure 2, the number of publications on the IoT and its components (i.e., smart objects, connected objects, smart apps, and mobile apps) has significantly increased since 2010, particularly since 2015, thereby indicating a growing interest regarding this topic from

researchers in all disciplines. For example, the number of publications on the IoT in peer-reviewed journals increased from 16 between 2010 and 2014 to 114 since 2015. However, the number of publications on smart and connected objects in peer-reviewed journals remained very small between 2010 and 2014 (9 publications) and then since 2015 onward (12 publications). Figure 3 depicts the number of publications on the topic in marketing.

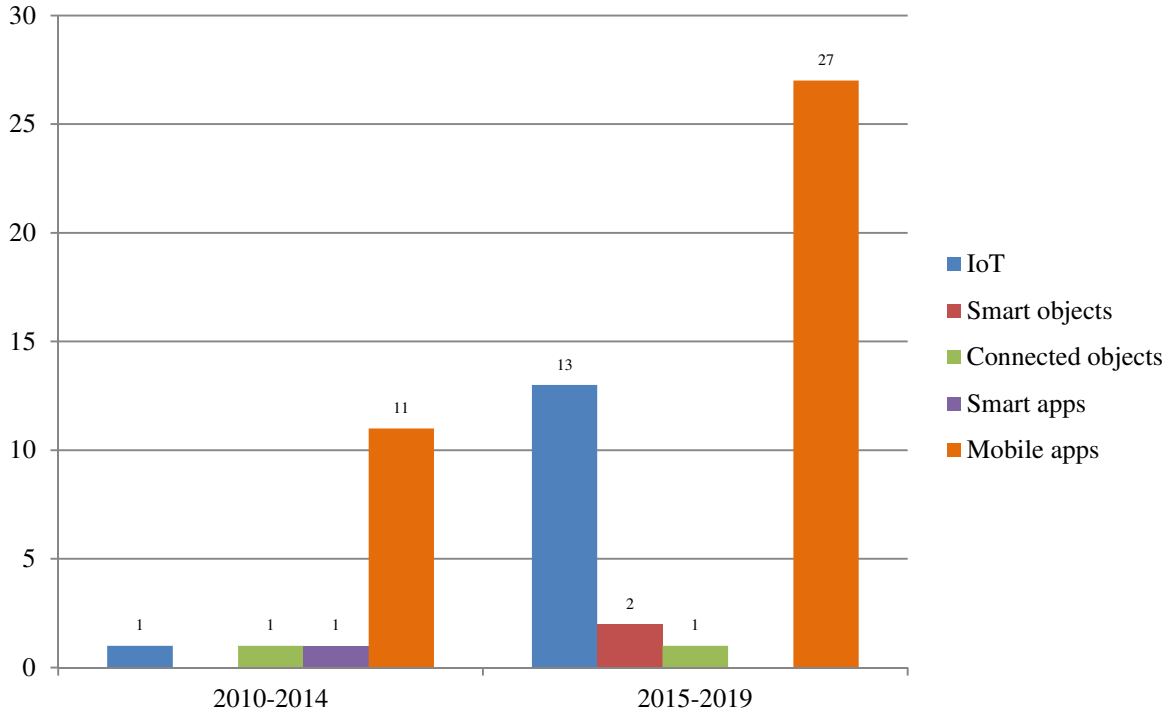


Figure 3: The number of publications on the IoT in marketing literature

Figure 3 indicates that the number of publications on the IoT in marketing literature is lower. Although there is a greater increase in the number of peer-reviewed articles on mobile apps, the number of publications on the IoT and smart technologies tends to increase as well. For example, the number of publications on the IoT in peer-reviewed journals increased from one publication between 2010 and 2014 to 13 publications since 2015. Further, the number of publications on smart and connected objects in peer-reviewed marketing journals remained weak between 2010 and 2014 (2 publications) and since 2015 onward (3 publications).

In the literature, among the factors affecting the acceptance of the IoT and smart technologies, the influence of the environment, organization, and the security of the technology have been highlighted (Hsu & Yeh, 2017); however, the authors recommended using other qualitative methodology to identify new antecedents (Hsu & Yeh, 2017). Besides, to study the acceptance of smart home devices, Kim et al. (2017), used traditional antecedents such as

perceived usefulness, enjoyment, and facilitating conditions, with others, like perceived sacrifice with technicality, perceived fee, privacy risk, innovation resistance, and variety seeking; but, the small amount of participants and the biases coming from the methodology limit the generalization of these results (Kim et al., 2017). Similarly, Canhoto and Arp (2017) studied the adoption of health and fitness wearables, and highlighted antecedents linked to the technology itself (functional features, access to the data, look and size, price), to the context (social influence, financial motivations), and to the user (perceived affinity to technology) (Canhoto & Arp, 2017); further, the authors recommended using a greater sample from other countries and generations, as well as a quantitative longitudinal study (Canhoto & Arp, 2017). In addition, Mani and Chouk (2017) worked on the resistance to smartwatches and showed that user resistance is influenced by the technology itself (perceived usefulness, price, novelty, visual aesthetics) and by the user (privacy concerns, intrusiveness, dependence, self-efficacy); the authors showed the importance to study other cultures and other technologies to find other antecedents (Mani & Chouk, 2017). Finally, Wunderlich et al. (2019) decide to mix qualitative and quantitative methods to highlight antecedents such as motivation (attitude, internal, external and introjected perceived locus of control), users' characteristics (age, education, income, family size), electricity consumption (consumption and costs, history of electricity providers), perceived privacy risk, and innovativeness; the researchers recommend to study other countries (Wunderlich et al., 2019) and to do longitudinal studies (Brown & Venkatesh, 2005; Wunderlich et al., 2019). Appendix 1A sums up the main articles on the acceptance of the IoT and smart technologies in marketing literature, based on the number of citations (i.e., above 20) or the rank of the journal (i.e., ranks 1, 2 or 3).

Research on the IoT and smart technologies is highly recommended to fill in various research gaps (Foroudi et al., 2018; Oh et al., 2007; Verhoef et al., 2017). Thereby, these research gaps lead our research goals and contributions for this thesis. Firstly, researchers recommend to conduct other studies in various countries (Canhoto & Arp, 2017; Wunderlich et al., 2019), with different generations (Canhoto & Arp, 2017), and various contexts of study (Mani & Chouk, 2017). Secondly, longitudinal studies are suggested (Brown & Venkatesh, 2005; Canhoto & Arp, 2017; Wunderlich et al., 2019) and with real objects to limit biases of interpretation (Kim et al., 2017). Thirdly, mixing qualitative and quantitative studies are highly suggested to better understand the adoption process (Canhoto & Arp, 2017; Wunderlich et al., 2019).

A. The antecedents of acceptance and usage of technologies

There is an increase in the acceptance of the IoT and smart technologies in recent decades, thereby also increasing opportunities for profits for companies (Pister, 2011). In the literature, little is known about the acceptance and usage of the IoT and smart technologies and about their consequences on consumer perceptions and behaviors (Foroudi et al., 2018; Oh et al., 2007; Verhoef et al., 2017). Technologies are associated with both benefits and risks that, in turn, become reasons for adoption or rejection; therefore, identifying the best conditions for consumer acceptance is a high-priority research issue (Verhoef et al., 2017). The literature contains different theories and models on technology acceptance.

In the literature, the innovation diffusion theory (IDT) from Rogers (1962) is the oldest theory explaining technology adoption. Even though it has been successfully used in various contexts, it does not focus on technology rejection or on user characteristics (Rogers, 1962). In 1967, Fishben and Ajzen (1967) introduced the theory of reasoned action (TRA), which is also tested and successfully applied in various contexts (Fishbein & Ajzen, 1975), however, it is not falsifiable (Ogden, 2003). In 1971, Triandis (1971) introduced the theory of interpersonal behavior (TIB) with, for the first time, emotional antecedents and, thus, an additional explanatory value (Milhausen et al., 2006); the TIB still lacks other antecedents that must be studied (Thompson et al., 1991). Then, in 1985, Ajzen (1985) defined the theory of planned behavior (TPB), which is used in various contexts (Courneya et al., 2000) but lacks external validity (Sniehotta, 2009) and does not study emotions (Sniehotta, 2009). One year after, Davis (1986) published the technology acceptance model (TAM), which remains the most influencing theory (King & He, 2006; Venkatesh et al., 2003) due to valid and reliable scales (Hendrickson et al., 1993) and a robust and significant model with strong psychometric properties (King & He, 2006; Lederer et al., 2000; Legris et al., 2003). However, the TAM shows a lack of practical value (Chuttur, 2009) and does not study certain antecedents, such as the influence of social and user characteristics (Bagozzi, 2007). In 1986, Bandura (1986) introduced the social cognitive theory (SCT), supported in various contexts (Bandura, 1986), that focuses more on environments than on emotions and personalities (Myers, 2010). That same year, Scherer (1986) defined the matching person and technology model (MPTM), which enables a comparison of technologies with reliable constructs; however, this theory is adapted to the health care sector and to the US/Canadian market (Scherer & Craddock, 2002). In 1991, Moore and Benbasat (1991) defined a 34-item

instrument with seven scales and acceptable levels of reliability to study technology adoption; however, their study context is too specific to be generalized to various fields (Moore & Benbasat, 1991). Besides, Thompson et al. (1991) formulated the PC utilization model (PCUM), which is supported in various researches (Davis et al., 1989) but lacks generalization regarding the context of study and the measure of affect (Thomson et al., 1991). Then, Davis et al. (1992) differentiated extrinsic and intrinsic motivations with the motivation model (MM), but the impact of enjoyment with PU and usage intentions needs to be examined more deeply (Davis et al., 1992). In 1995, Taylor and Todd (1995) combined the TAM and TPB to strengthen the theory and overcome certain issues related to the TAM and the TPB (Mathieson, 1991); however, there is an issue of self-generated validity (Feldman & Lynch, 1988). Further, Venkatesh and Davis (2000) formulated the TAM 2, highlighting the role of social influence but with no structural equation modelling (Venkatesh & Davis, 2000). This same year, Parasuraman (2000) formulated the technology readiness index (TRI), a cross-culturally valid instrument, but the low model fit indices showed that research must be deepened in this area of study (Parasuraman, 2000). In 2003, the unified theory of acceptance and use of technology 1 (UTAUT1) (Venkatesh et al., 2003) was formulated. Even though the UTAUT1 is supported in various contexts (El-Gayar & Moran, 2006), it is too complex for predicting intentions (Bagozzi, 2007), and it lacks emotional antecedents (Venkatesh et al., 2012). The attitude of intention to use model (AIM) (Curran & Meuter, 2005) brings out new insights but, according to both authors, the model is only significant in banking contexts. In 2008, Venkatesh and Bala (2008) improved the TAM 1 and TAM 2 and formulated the TAM 3 by studying antecedents of PEU and the role of perceived enjoyment; however, there is a lack of theoretical validations regarding the evolution of acceptance over time (Venkatesh & Bala, 2008). In 2010, Beaudry and Pinsonneault formulated the coping model of user adaptation (CMUA), which focuses on positive and negative emotions associated with technology; however, it is not applicable to all contexts of study and more longitudinal studies are required (Beaudry & Pinsonneault, 2010). Then, Venkatesh et al. (2012) enhanced the UTAUT1 and formulated a UTAUT2 by adding hedonic motivations; however, user characteristics are not considered and the sample distribution must be improved (Venkatesh et al., 2012). Finally, Lowry et al. (2013) published the hedonic-motivation system adoption model (HMSAM), which highlights the main role of enjoyment; however, other motivations and contexts of study require being studied (Lowry et al., 2013; Barnes, 2007).

In the context of the IoT, certain variables appear to be interesting and warrant further investigation, such as the relevance of usefulness factors and enjoyment antecedents (Triandis, 1971; Bandura, 1986; Venkatesh & Bala, 2008; Venkatesh et al., 2012; Lowry et al., 2013) as well as social factors (Triandis, 1971; Bandura, 1986; Moore & Benbasat, 1991; Venkatesh & Davis, 2000; Venkatesh et al., 2003). One antecedent not studied with these researches is the concept of privacy concerns; it is only mentioned with IoT technologies (see Appendix 1A and 1B). Further, this thesis aims to study the research gaps indicated by the literature. This thesis digs into the technology acceptance literature by studying antecedents of the adoption of IoT and smart technologies owing to preliminary qualitative studies with SCO, smart apps (sleep apps), and smart environments (smart homes and smart stores). These qualitative studies are further developed with quantitative studies to build theoretical models with relevant constructs according to different IoT components (e.g., smart objects, smart apps, and smart environments). Therefore, another theoretical contribution is to show the relevance of the TAM enriched with new and rarely investigated variables such as perceived well-being, perceived social image, privacy concerns, and types of personalities. Appendix 1B presents the main technology acceptance studies and theoretical models in the literature, along with the research gaps that must be considered.

B. The consequences of the IoT and smart technologies on perceived well-being

The IoT and smart technologies are leading to important changes in consumer behavior and health practices (Brennan, 1999). Connected sensors can help detect illnesses or measure atmospheric variables like the level of air quality. Therefore, the main promise of the IoT is to enhance consumer well-being (Atzori et al., 2010; Etzioni, 1999; Harkin et al., 2016; Kluger & DeNisi, 1996; Porter & Heppelmann, 2014; Xia et al, 2012), and to provide users with a better quality of life (Xia et al, 2012). Marketers can determine the needs and interests of consumers to offer them better satisfaction (Kotler et al., 2002). Further, consumers mostly make decisions with the goal of maximizing the perceived well-being of consumers (Mogilner et al., 2012). Perceived well-being seems to have many and different definitions according to the literature. In economics, perceived well-being is traditionally measured through materialistic and monetary indicators (i.e., income) (Penn, 2009). In social sciences, perceived well-being can rely on two approaches, whether on hedonism linked to pleasure, happiness and positive emotions, or on eudemonism linked to abilities to find a purpose, be in control

and have positive relationships with others (Ryan & Deci, 2001). Table 1 defines the concept of perceived well-being from the literature, with the components leading to our definition.

Author(s), date	Definition(s) of well-being	Components leading to our definition of perceived well-being
Larson, 1978	<ul style="list-style-type: none"> - Categories: health, socioeconomic and social activity factors - “A shared core of something that can be called subjective well-being” 	<ul style="list-style-type: none"> - Health - Social activity - Subjective feeling
Sirgy, 2001	<ul style="list-style-type: none"> - Senses of well-being: life satisfaction, quality of life, overall happiness, subjective well-being - Actual well-being: objective indicators of economic, social, environmental well-being 	- Consumer’s sense of well-being (life satisfaction, quality of life, happiness, subjective well-being)
Lee et al., 2003	- Perceived social, economic, medical, spiritual, psychological conditions	<ul style="list-style-type: none"> - Social - Medical - Psychological
Veenhoven, 2003	- A state characterized by enjoyable feelings and positive judgements	<ul style="list-style-type: none"> - Enjoyable feelings - Positive judgements
Gibbs, 2004	- Well-being spans both moral and prudential aspects of life	<i>Not usable in this context</i>
Sirgy & Lee, 2004	- A desired state of objective and subjective well-being involved in the various stages of the consumer/product life cycle, in relation to consumer goods	<ul style="list-style-type: none"> - Desired state - In relation to consumer goods
Sirgy & Lee, 2006	<ul style="list-style-type: none"> - Cognitive well-being: if consumers believe they are fine (life satisfaction) - Affective well-being: if consumers feel well (happiness) 	<ul style="list-style-type: none"> - Satisfaction - Happiness
Kahneman & Deaton, 2010	- The frequency and intensity of experiences of joy, fascination, anxiety, sadness, suffering and affection that	<ul style="list-style-type: none"> - Experiences - Emotions

Author(s), date	Definition(s) of well-being	Components leading to our definition of perceived well-being
	make people's life pleasant or unpleasant	
Burroughs & Rindfleish, 2011	- Aligning individual and societal needs (i.e. physical, psychological, economic, social) in relation to consumption	- In relation to consumption
Mick et al., 2012	- A state of flourishing that involves health, happiness and prosperity	- Health - Happiness
Anderson et al., 2013	- Dimensions: access, literacy, consumer involvement, respect, support, and social networks at individual, collective, and ecosystem levels	- Consumer involvement - Social networks - Individual level
Haws et al., 2016	- Trade-off between short-term pleasure and long-term positive outcomes	- Short-term pleasure - Long-term positive outcomes
Kim & Kim, 2017	- Major perspectives: subjective, eudemonic, social well-being	- Subjective well-being
Ayadi et al., 2019	- A subjective state of fullness resulting from judgments, emotions and aspirations about the perception of a current situation, compared to a past or future of the person or entourage - 3 components: cognitive (perception of their own lives with the satisfaction of financial aspects), affective (positive emotions such as happiness) and conative (what people want and plan to do according to their aspirations) - 4 dimensions: psychological, physical, financial, social	- Subjectivity - From judgements, emotions, aspirations - Cognitive, affective, conative components

Table 1: Definitions of the concept of consumer well-being in the literature

According to the definitions from the literature presented in Table 1, we define perceived well-being in the context of B2C, in the following manner: “A *desired state of objective and subjective well-being related to a better health, social activity, happiness, contentment, fulfilment, involvement, and quality of life leading to positive judgements and emotions toward choices of consumption and long-term positive consequences*”.

Research on well-being was initiated in 1917 and 4,010 peer-to-peer review papers have been published on the subject in various fields such as health, consumer research, economics, society, business, ethics, or psychology. Figure 4 presents the number of reviewed publications on well-being in all disciplines, according to Business Source Complete database.

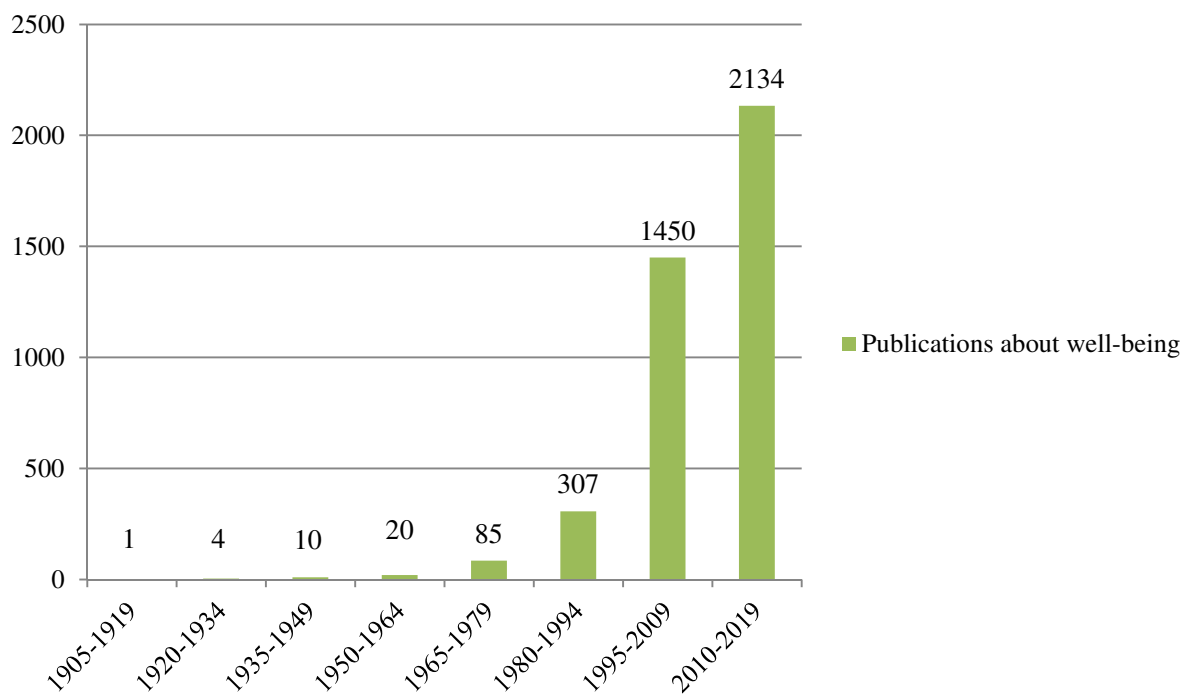


Figure 4: Number of publications on well-being in all disciplines

Figure 4 indicates that the number of published peer-to-peer review papers on well-being has considerably increased over previous decades in all disciplines (economics, health, consumer research, society, business, ethics, or psychology), thereby indicating a growing interest in this subject.

Further, Figure 5 depicts the number of publications on consumer well-being in marketing literature. In marketing, consumer well-being research began in 1972, with 85 papers published since.

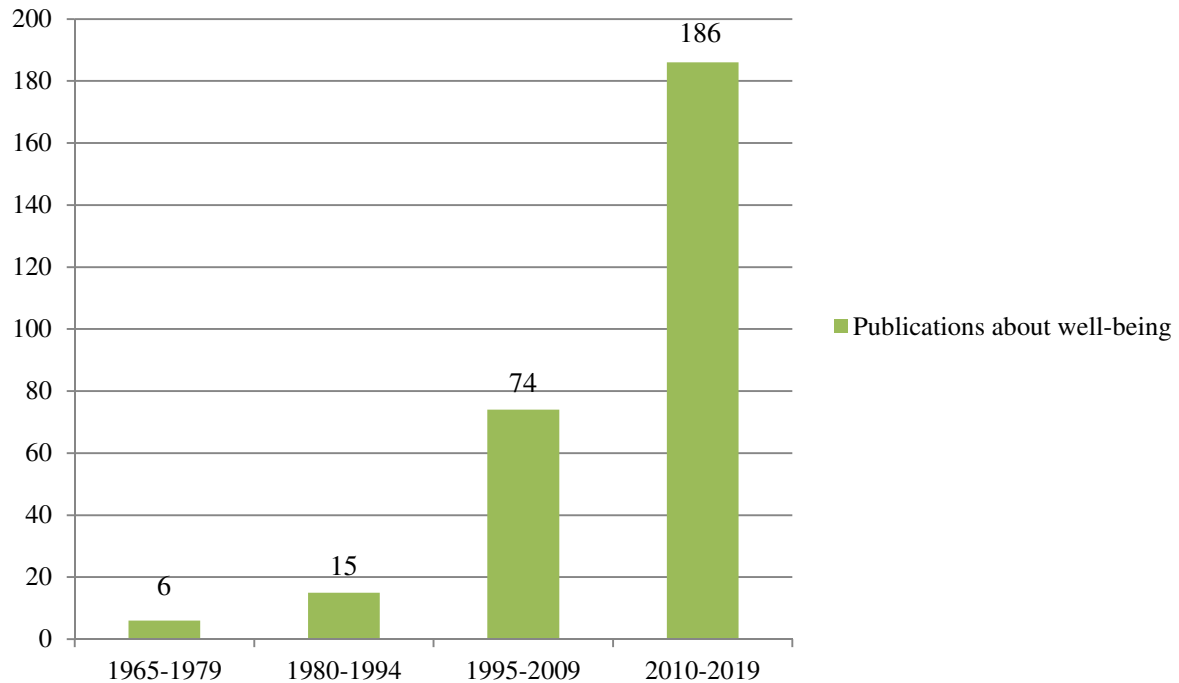


Figure 5: Number of publications on consumer well-being in marketing literature

Figure 5 indicates that consumer well-being is a growing research topic in marketing as well. From 2009 to 2019, the number of articles doubled (74 publications to 186).

In 2010, Singh and Arora explored the antecedents of individual well-being, but the authors recommended studying cultures other than India and other antecedents (Singh & Arora, 2010). Further, in 2012, Bone et al. focused on finances and social status linked to consumer well-being and linked emotions to social expectations; however, they highlight the importance of increasing the sample size (i.e., $N = 39$) and to study other antecedents as well (Bone et al., 2012). Higgsa and Dulewicz (2014) related personality and emotional intelligence to well-being, but this explains only 20% of the variance of perceived well-being, thereby showing the importance of pursuing transformative service research. Anderson and Ostrom (2015) highlighted transformative service research (TSR) to define it as the manner in which services influence service success and, reciprocally, how services influence consumer well-being. They mentioned the need to deepen the link with consumer characteristics (Anderson & Ostrom, 2015). Ahmadpour et al. (2016) study passengers' attitudes in airplanes with real-

time flight experiences, thereby highlighting reluctance factors; however, the small number of participants ($N = 16$) and the lack of data regarding passenger activities during the flight does not allow a generalization of these results (Ahmadpour et al., 2016). Then, Hsieh et al. (2016) interviewed 602 customers of travel agencies to deepen research regarding well-being and services, thereby revealing the importance of offering high-quality services to consumers. However, they focused only on this industry and did not study other antecedents and issues present in other contexts (Kyriakopoulos & Moorman, 2004). Then, in 2016, Kasnakoglu combined qualitative and quantitative studies to explore the link between well-being and co-creation in order to improve services; however, the author recommended studying other contexts of study and conducting longitudinal studies to improve the validity of results (Kasnakoglu, 2016). Umans et al. (2016) conducted quantitative research with 207 Swedish auditors to deepen the link between well-being and collectivistic organizational culture; the authors suggested exploring other antecedents like personalities (Umans et al., 2016). In addition, Netemeyer et al. (2017) deepened the concept of financial well-being, showing that finances influence well-being, even though other types of well-being must also be studied as well (Netemeyer et al., 2017). In France, Gonzalez et al. (2017) studied the link between the perceived value of the distribution channel and well-being through utility, hedonism and social values. The authors suggested exploring other contexts of study and other antecedents with longitudinal studies (Gonzalez et al., 2017). Lastly, Bhat et al. (2019) conduct a literature review of 94 articles on social marketing and well-being to classify well-being; the authors recommend using mixed research approaches and longitudinal studies to explore behavior change (Bhat et al., 2019). Appendix 1C sums up the main published articles on consumer well-being in marketing, according to the number of citations and rank of the journal.

Research showed that a better well-being is impacted by the ease of use of self-tracking, self-knowledge and self-management of SCO (Ahern et al., 2006; Gustafson et al., 2002; Gibbons et al., 2011). However, the direction of the relationships between technology adoption and well-being is not clear in the existing literature (Steptoe et al., 2012). On the one hand, hedonic motives appear to be relevant antecedents of technology adoption in consumer contexts (Bruner & Kumar, 2005; Childers et al., 2001; Dabholkar & Bagozzi, 2002; Hirschman & Holbrook, 1982; Kim & Forsythe, 2008; Kulviwat et al., 2007; Van der Heijden, 2004). On the other hand, Etkin (2016) shows that using smart health devices decreases well-being in the long term due to the consequences of technology dependence and stress. Indeed, tracking activities (i.e., number of steps) through quantified-self leads to

increased stress because people perceive this activity as a duty and not as fun (Gonzalez et al., 2017). Therefore, reduced well-being leads to a decrease of engagement in the activity. Since the results in the literature related to the impact of smart objects on perceived well-being are mitigated, further research in this regard is highly recommended (Anderson et al., 2013; Arora et al., 2017; Kim et al., 2016; Krebs & Duncan, 2015). Thus, this thesis also studies the link between perceived well-being and IoT and smart technologies.

In 2013, Van Ittersum et al. studied how real-time spending feedback influenced positive feelings during shopping; the authors suggested deepening research on other feedback and behavior (Van Ittersum et al., 2013). Chiu et al. (2014) explored the link between well-being and the ergonomic design of smart technologies with Bluetooth earphones; they recommended studying other contexts and variables and conducting longitudinal studies (Chiu et al., 2014). Further, Fang et al. (2014) explored the impact of mobile money services on consumer well-being; the authors suggested reproducing their study with a larger sample (i.e., $N = 35$) and in the context of countries other than Cambodia (Fang et al., 2014). Sanzo-Perez et al. (2015) published a paper on the influence of social innovations—such as for-profit and non-profit organizations and co-creation activities—on well-being. The authors highlighted limits regarding the categories of innovations considered together and the need to study moderators (Sanzo-Perez et al., 2015). In 2017, Linnhoff and Smith examined the influence of mobile app usage on life satisfaction. The researchers revealed that frequency decreases well-being while social media increases well-being, thereby highlighting the need to better understand how mobile app usage influences well-being, or personality influences the manner in which people use mobile apps (Linnhoff & Smith, 2017). Moreover, research has shown that frequency of use increases PEU, PU, and well-being through higher feelings of power (Teh et al., 2017) but that all generations must be targeted, particularly the youngest (Teh et al., 2017). Then, Munzel et al. (2018) showed that well-being can be influenced by the manner in which people use social networks and, more precisely, the size and intimacy of their social networks (Munzel et al., 2018); the authors also emphasized that other antecedents must be investigated, such as usage intensity (Valkenburg & Peter, 2009) or privacy concerns (Jiang et al., 2013). In 2019, Hasan et al. show that enjoyment is the stronger determinant of intention to use technology and they suggest creating hybrid models, and to study countries other than Bangladesh (Hasan et al., 2019). Appendix 1D sums up the main published articles about the link between technology and well-being in marketing, according to the number of citations and rank of the journal.

Therefore, this thesis positions itself in the research stream related to consumer well-being and aims to study the link between user's well-being and the acceptance of the IoT and smart technologies (e.g., smart objects and smart applications). In terms of the research gaps, the studies we developed for this thesis consider new variables, such as personalities and emotions (Anderson & Ostrom, 2015), with empirical and mixed research approaches (Bhat et al., 2009), and sufficient respondents from France (Fang et al., 2014). One of these studies is also a longitudinal study conducted to understand users' perceptions before and after use and compare the evolution of the relationships among the variables (Berry, 1995). Moreover, we adapt a well-being scale from the literature (Luca & Suggs, 2013), which is significant in our context of study. Finally, we focus on specific technologies (Kyriakopoulos & Moorman, 2004): article 1 differentiate SCO, sleep apps, smart homes, and smart stores; articles 2 and 6 deal with SCO, articles 3 and 7 are about smart apps (i.e., a sleep app), article 4 is on smart homes, and article 5 is related to smart stores.

THESIS PLAN

This thesis includes two main parts with six chapters (see next page).

Chapter 1 elaborates a definition of the IoT and smart technologies, based on a literature review of 134 articles about the IoT and SCO, 14 of them coming from the marketing literature. This is completed by qualitative and quantitative surveys in chapter 2.

Chapter 2 presents a theory of the antecedents of the acceptance and usage of the IoT technology and components with qualitative studies about SCO, smart apps (sleep apps) and smart environments (smart homes, and smart stores), and quantitative studies about these same contexts too.

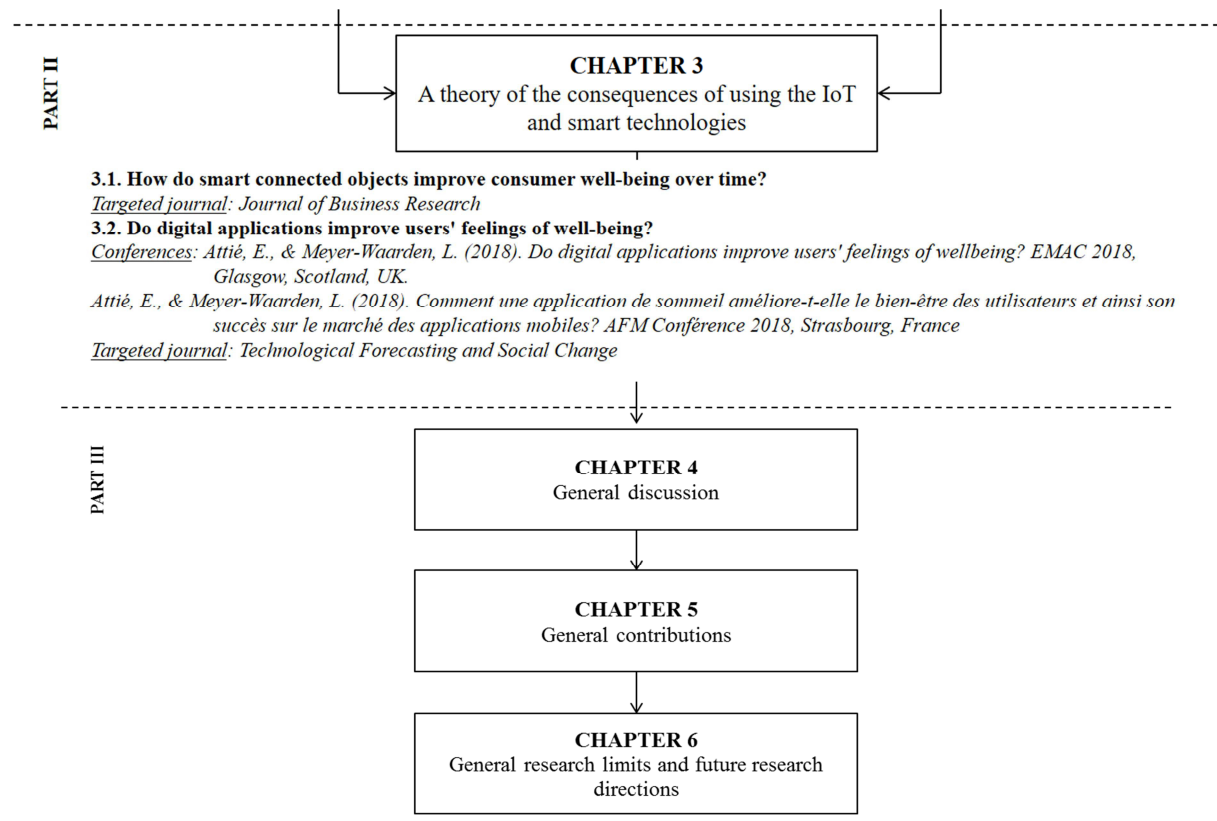
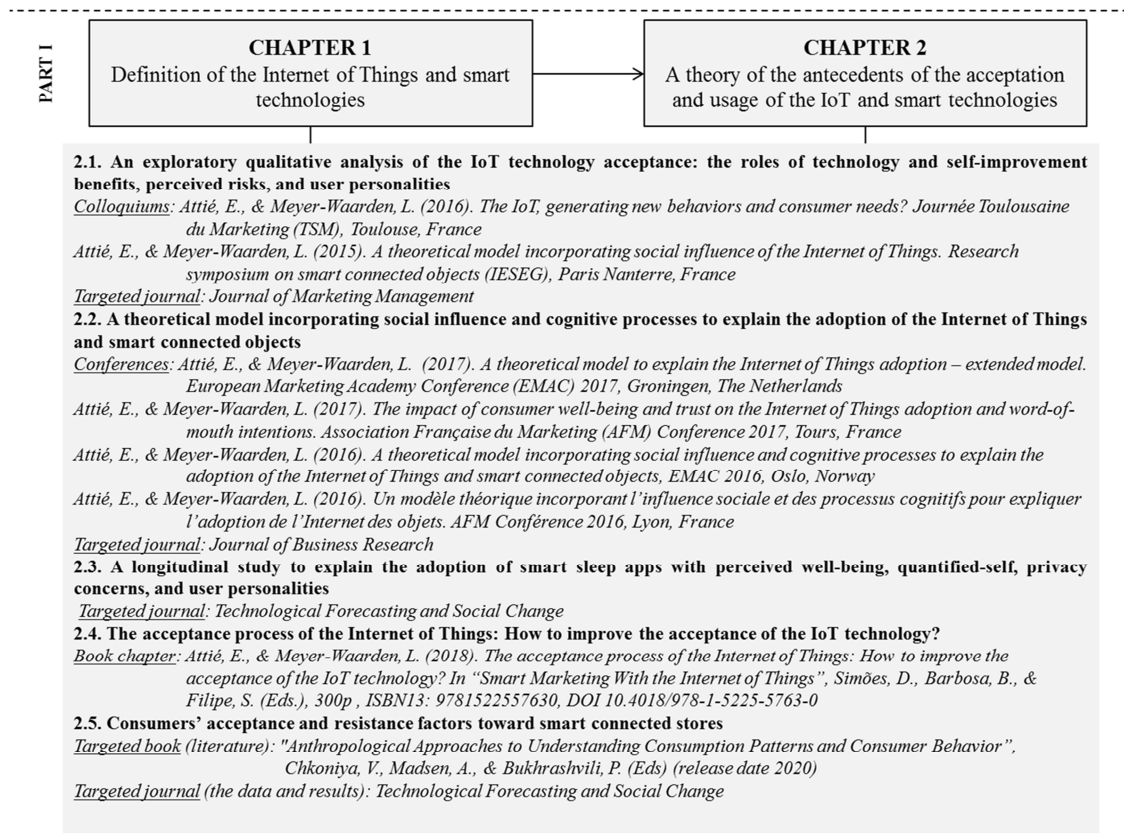
Chapter 3 then presents a theory of the consequences of the adoption of the IoT and smart technologies with a quantitative study about the influence of using SCO over three years of use, and a second longitudinal quantitative study with a smart app.

Chapter 4 gives a general discussion regarding our results about the acceptance and consequences of the IoT technology.

Chapter 5 shows the theoretical, managerial and methodological implications of our research.

Finally, Chapter 6 shows the limits of our research and gives future research directions.

PART I



The main goal of this part is to deepen the understanding of the acceptance and adoption processes of the IoT and smart technologies. To do this, four contexts of study are explored: SCO, smart sleep apps, and smart environments with smart homes and smart stores. Our first article explains a preliminary qualitative exploratory research about each context of study. The other studies are quantitative researches that deepen the qualitative findings with conceptual models built according to the literature. Results show that utility benefits are the first antecedents of the IoT and smart technologies acceptance, through perceived usefulness and perceived ease of use. Once consumers accept to use the technology, self-improvement and well-being benefits are the reasons of loyalty to use, through perceived well-being and perceived social image. Yet, perceived risks and fears about the way the collected data is used are the main barriers to using the IoT and smart technologies. These obstacles can be compensated by a higher utility value, through personalization benefits for example (Dimitriadis & Kyrezis, 2010). Using the IoT technology implies an ongoing process of value creation from both users and companies (Benamar et al., 2019). Acceptance and adoption also depend on users' personality traits since each consumer is unique and thus, their perceptions and behaviours differ as well. The first chapter of part I defines the concept of the IoT and smart technologies, according to research. Then, the second chapter examines the antecedents of acceptance and usage of the IoT and smart technologies with five articles:

1. An exploratory qualitative analysis of the IoT technology acceptance: the roles of technology and self-improvement benefits, perceived risks, and user personalities (*Article 1; section 2.1.*)
2. A theoretical model incorporating social influence and cognitive processes to explain the adoption of the Internet of Things and smart connected objects (*Article 2; section 2.2.*)
3. A longitudinal study to explain the adoption of sleep apps with the TAM, perceived well-being, quantified-self, privacy concerns and different types of personalities (*Article 3; section 2.3.*)
4. The acceptance process of the Internet of Things: How to improve the acceptance of the IoT technology? (*Article 4; section 2.4.1.*)
5. Consumers' acceptance and resistance factors toward smart connected stores (*Article 5; section 2.4.2.*)

CHAPTER 1: DEFINITION OF THE INTERNET OF THINGS AND SMART TECHNOLOGIES

Introduction to Chapter 1

This thesis aims to define the concept of the IoT and smart technologies. The IoT cannot be reduced to a materiality or a technology with only SCO; the label is too simplistic next to the entire ecosystem. The next paragraph and subsections define the IoT and its components included in a wide IoT ecosystem (see Figure 6).

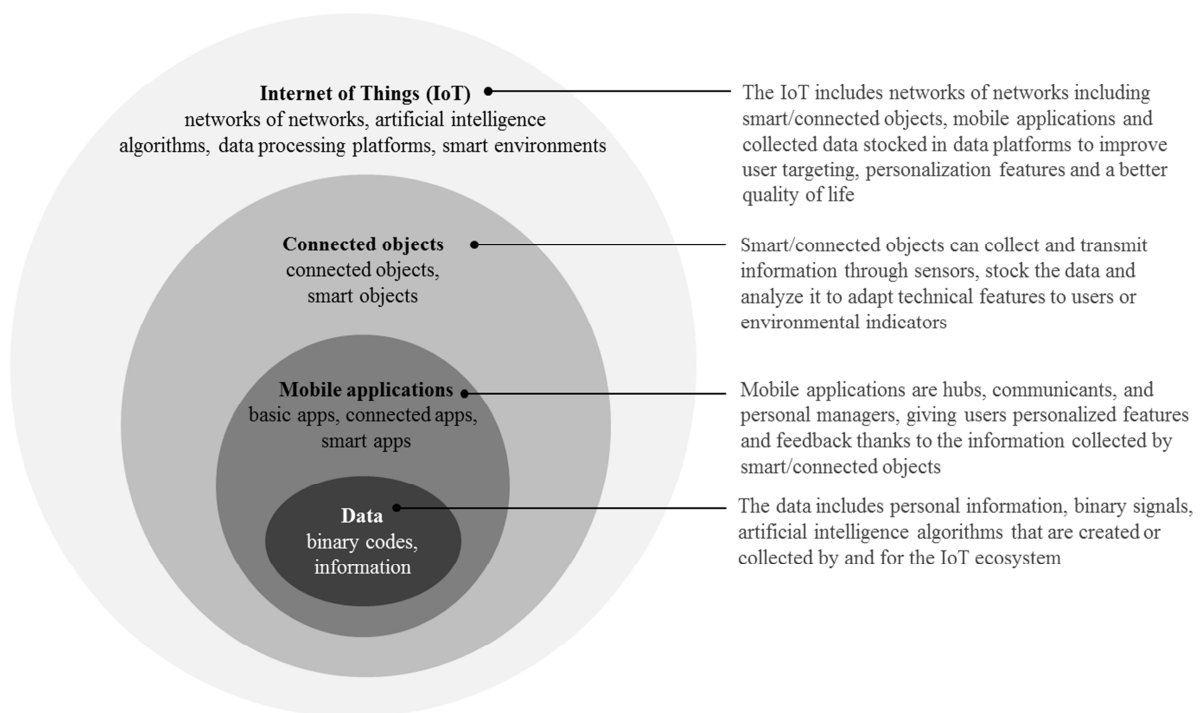


Figure 6: Classification of the IoT

Figure 6 indicates that the IoT includes networks, artificial intelligence, data platforms, smart/connected objects, mobile apps and data. The data is defined as series of codes leading to meaningful information (Beynon-Davies, 2002). A data analysis allows a better use of smart technologies, enhancing knowledge and wisdom for both users (i.e., higher quantified-self and well-being) and companies (i.e., better customer knowledge for personalization, higher profits, and improved product and service development). The other components of the IoT are detailed in the next subsections.

1.1. The Internet of Things (IoT)

The IoT is a new way of interacting with objects, environments and people. Indeed, the IoT can connect everyone and anything, dependently or independently of the initial settings pre-set by users, according to artificial intelligence included in sensors, and can provide personalized feedback and features through SCO and mobile apps. Therefore, the IoT includes physical objects capable of emitting data through sensors (i.e., connected objects, mobile apps, and sensors), virtual connecting things (i.e., artificial intelligence algorithms, and wireless networks) and platforms capable of collecting and stocking, then analyzing and transmitting data. The IoT remains a complex interconnected ecosystem and the definitions researchers have given since 1999 are continuously evolving (see Table 2).

Author(s)	Definitions and context	Components leading to our definition
Ashton, 1999, 2009, 2013	<ul style="list-style-type: none"> - The IoT allows us to make better and improve quality of life (1999) - The IoT is the development of the Internet (2009) - The IoT is the information companies can sell (2013) 	<ul style="list-style-type: none"> - Improve quality of life - A development of the Internet - Information
Dodson, 2003	“The IoT points out a new vision of technology: in the 19th century, machines learned to do, to create, to make; in the 20th century, they learned to think; and in the 21st century, they sense, and respond to either people or other connected objects”	<ul style="list-style-type: none"> - Evolution of consumer experience
International Technology Union, 2005	“The IoT can connect any object in a sensory and smart way by combining item identification (to tag things), sensors and wireless sensor networks (to feel things), embedded systems (to think things), nanotechnology (to shrink things)”	<ul style="list-style-type: none"> - Smart objects and sensors
The European Commission, 2008	“A world-wide network infrastructure of interconnected things with their own virtual identities and unique identifications, able to work anywhere, using smart interfaces to connect and communicate in a social, environmental, and consumer context”	<ul style="list-style-type: none"> - World-wide network infrastructure of interconnected things

Author(s)	Definitions and context	Components leading to our definition
Atzori et al., 2010	“The IoT gives a new vision of being connected anytime, anywhere, with any media and anything. The main power of the IoT is its impact on everyday life and thus on consumers' behaviors”	- Impact on everyday life and on consumer behavior
Tarkoma & Katasonov, 2011	“The IoT represents a global network and service infrastructure of variable density and connectivity with self-configuring capabilities based on standard and interoperable protocols and formats consisting of heterogeneous things that have identities, physical and virtual attributes, and are seamlessly and securely integrated into the Internet”	<ul style="list-style-type: none"> - Global network and service infrastructure - Physical and virtual attributes - The Internet
Gartner & McKinsey & Company, 2012	“The IoT should transform considerably the way of living of consumers in the next years”	- The IoT should transform people’s way of living
Gubbi et al., 2013	“The IoT paradigm implies any objects that can connect to an Internet network anytime, anywhere and for anyone, transforming the classic Internet into a fully integrated internet”	- An integrated network
Boos et al., 2013	“The IoT technology can inform, automate actions and transform things and visions”	- Transform things and visions
Hoffman & Novak, 2015, 2018	<p>“The IoT is a thrilling next phase in the Internet revolution because it brings the intelligence of the Internet to physical products with the potential for something new to emerge”</p> <p>“The IoT is an interconnected environment made of invisible networks of networks that can collect, analyze and store data, control connected objects which then interact with people or other physical or virtual things”</p>	<ul style="list-style-type: none"> - The intelligence of the Internet - Something new to emerge - Network of networks - Role between the data, connected objects, and people

Table 2: Definitions of the IoT from literature

In this thesis, we contribute to this discussion between researchers and we define the IoT as *“a network of networks which includes smart/connected objects, mobile applications and collected data stocked in data platforms to improve user targeting, and personalization features for better consumer experience and quality of life”* (Attié & Meyer-Waarden, 2018).

1.2. Smart/connected objects

Smart/connected objects represent the physical aspect of the IoT. They are monitored by remote controls and real-time data hubs, like smartphones, tablets, or connecting robots such as Google Home or Alexa from Amazon. Table 3 outlines how smart/connected objects are defined in the literature.

Reference	Definition
IPSO Alliance, 2008	“Smart connected objects are small computers with sensors and communication devices, embedded in everyday objects”
Popescul & Georgescu, 2013	“Physical things can connect to other physical or virtual things, using wireless communication and thus offering services”
O’Brien, 2015	“Smart wearables are embedded with Internet connectivity, directly via sensors embedded in the device”
Ledger, 2014	“Smart wearables are embedded with Internet connectivity, indirectly by connecting with a smartphone”
Weber, 2016	“IoT wearables have data collection, storage and transmission capabilities”
Hoffman & Novak, 2015	“The collection of everyday objects and devices in the physical environment that are embedded with technology including sensors, actuators that are programmable and have the ability to communicate wirelessly with the Internet. These “smart products” interact and communicate with themselves and each other —and with humans— by sending and receiving the data through the Internet that is stored and organized in a database”
Hsu & Lin, 2016	“Smart objects are regarded as a physical embodiment with communication functionality, possessing a unique identifier, some basic computing capabilities and a way to detect physical phenomena and to activate actions having an effect on physical reality”

Reference	Definition
Mani & Chouk, 2017	“Smart products have: (1) ‘sensors’ that collect data about the environment; (2) ‘actuators’ that activate an action and are controlled by some other entity, (3) ‘network connectivity’ that can take several forms, including Wi-Fi, Bluetooth or RFID”

Table 3: Definitions of SCO from literature

In this thesis, we contribute to this discussion and define connected objects as “*devices that communicate through connected remote controls (e.g., smartphones, and tablets), get the data from sensors, and analyze this information to transmit it to users so they can manage all the technical features*” (Attié & Meyer-Waarden, 2018). We differentiate between connected objects and smart objects which are “*connected objects with an artificial intelligence enabling the technology to automatically react to external indicators (i.e., temperature, user’s timetable, etc.) without the necessary help or request of users*” (Attié & Meyer-Waarden, 2018). Indeed, connected objects are said to be ‘smart’ if they are also active, autonomous, and cognitive (Poslad, 2009).

1.3. Mobile applications

The mobile app category comprises ‘basic’, ‘connected’, and ‘smart’ kinds of mobile apps which are defined below.

‘Basic’ apps are software programs developed to collect, store, and provide real-time data (Rakestraw et al., 2013) to respond to specific needs. For example, a texting app is a basic app since it allows users to get texts from other people, keep them and send texts back; thus, the functionalities of this app should be a 100% controllable by users.

A ‘basic’ mobile app becomes a ‘connected’ app once the app also collects the data through sensors. This data becomes valuable information about users (i.e., health rate, number of steps, geolocation, etc.) and/or environments (i.e., temperature, atmosphere pressure, production lines, etc.) in order to suggest personalized feedback and features. The connected app’s parameters are a 100% controlled by users. Mobile apps which count the number of steps is an example of connected apps: users can ask to check the number of steps done each day to reach their personal goals (e.g., Godinho et al., 2016).

A 'connected' app becomes a 'smart' app when the app includes artificial intelligence programs enabling the app to automatically suggest personalized advice (e.g., Rakestraw et al., 2013; Harleen et al., 2014) according to measured indicators, to spontaneously adapt its functionalities to users and environments indicators, and to update the data anytime, independently of users who thus have a low technical control. Smart apps automatically send the data to companies' external databases to improve the app's features, offer a personalized mobile experience and/or resale user information. An example of smart app is a sleep app, which is programmed to wake up users at the end of their last sleep cycle, sometimes earlier than their time initially programmed.

Conclusion to Chapter 1

This chapter defines the IoT and its smart technologies. Table 4 sums up our definitions made thanks to a literature review.

Concept	Definition
Internet of Things	<i>“The IoT is a network of networks which includes smart/connected objects, mobile applications and collected data stocked in data platforms to improve user targeting, and personalization features for better consumer experience and quality of life”</i>
Smart objects	<i>“Smart objects are connected objects which possess an artificial intelligence enabling the technology to automatically react to external indicators (i.e., temperature, user’s timetable, etc.) without the necessary help or request of users”</i>
Connected objects	<i>“Connected objects communicate through connected remote controls (e.g., smartphones, tablets), get data from sensors, and analyze it to transmit this information to users so they can manage all the technical features”</i>
Smart apps	<i>“Smart apps include artificial intelligence programs enabling apps to automatically suggest personalized advice according to measured indicators, to spontaneously adapt functionalities to users and environments indicators, and to update the data anytime, independently of users who thus have a low technical control”</i>
Connected apps	<i>“Connected apps collect data through sensors and this data becomes information about users and/or environments in order to suggest personalized feedback and features. The connected app’s parameters are a 100% controlled by users”</i>
Basic apps	<i>“Basic apps are software interfaces which also collect, store, and provide real-time data to respond to specific needs”</i>

Table 4: Summary of the definitions of the IoT and its smart technologies

CHAPTER 2: A THEORY OF THE ANTECEDENTS OF THE ACCEPTANCE AND USAGE OF THE IOT AND SMART TECHNOLOGIES

Introduction to Chapter 2

One main goal of this thesis is to better understand the acceptance and adoption processes of the IoT and smart technologies. Acceptance is defined as the willingness and intentions to integrate the use of a technology into a daily life (Bobillier-Chaumont et al., 2006). This acceptance process can lead to a rejection of the technology or an adoption (i.e., purchase and first use) then to usage (daily use of the technology) (Breton & Proulx, 2002). Thus, acceptance happens before use, and researchers look for favorable factors to better adapt technologies (Bobillier-Chaumont et al., 2006). In this thesis, we study acceptance, with intention to use, and usage, with real use.

This chapter 2 highlights the antecedents of acceptance according to a qualitative study then to the literature, which are followed by quantitative studies (see Figure 7). Here is a summary of our methodology and studies:

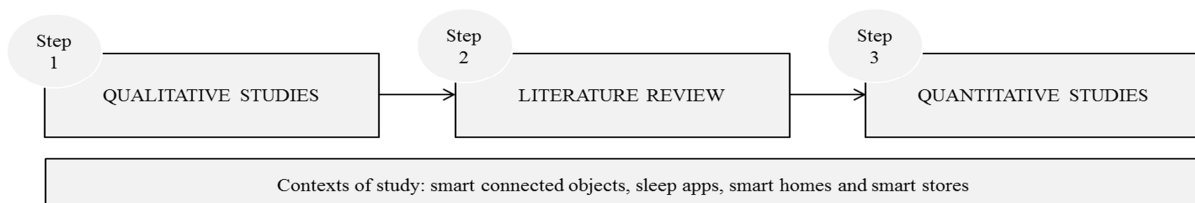


Figure 7: Summary of our methodology and contexts of studies (*Chapter 2*)

Figure 7 indicates that we start by qualitative studies to highlight relevant antecedents then guide ourselves through the literature. After a literature review, we test our findings with quantitative studies. Here are the different studies presented in this chapter:

1. An exploratory qualitative analysis of the IoT technology acceptance: “The roles of technology and self-improvement benefits, perceived risks, and user personalities” (*intended to be submitted to Journal of Marketing Management*). It highlights the antecedents of acceptance such as perceived usefulness, perceived ease of use, perceived well-being, perceived social image, privacy concerns, and personalities thanks to qualitative studies about SCO (study 1), a sleep app (study 2), and smart environments (smart homes (study 3) and smart stores (study 4)) (*Article 1; section 2.1.*)

2. Smart objects acceptance and adoption: “A theoretical model incorporating social influence and cognitive processes to explain the adoption of the Internet of Things and smart connected objects” (Attié, E., & Meyer-Waarden, L., paper presented at EMAC 2017 Groningen, AFM 2017 Tours, EMAC 2016 Oslo, AFM 2016 Lyon; intended to be submitted to *Journal of Business Research*). It shows that utility benefits and personality traits are the main reasons leading to acceptance, and perceived well-being and social recognition lead to loyalty of use, whereas privacy concerns are the main obstacles to the adoption of SCO (Article 2; section 2.2.)

3. Smart apps acceptance and adoption: “A longitudinal study to explain the adoption of sleep apps with the TAM, perceived well-being, quantified-self, privacy concerns and different types of personalities” (intended to be submitted to *Technological Forecasting and Social Change*). It shows that the Technology Acceptance Model (TAM; Davis, 1989) main variables (e.g., perceived usefulness, perceived ease of use, intention to use, real use) are relevant in the adoption process of a sleep app, along with new and few investigated variables, such as perceived well-being, quantified-self, privacy concerns, and types of personalities (Article 3; section 2.3.)

4. Smart environments acceptance: “The acceptance process of the Internet of Things: How to improve the acceptance of the IoT technology?” (Attié, E., & Meyer-Waarden, L., book chapter published in “*Smart Marketing With the Internet of Things*” (2018), Simões, D., Barbosa, B., and Filipe, S. (Eds.), 300p) (Article 4; section 2.4.1.) followed by “Consumers’ acceptance and resistance factors toward smart connected stores” (Attié, E., Meyer-Waarden, L., & Bachié, E., chapter submitted in “*Anthropological Approaches to Understanding Consumption Patterns and Consumer Behavior*” currently under minor revisions in December 2019 for the literature and managerial recommendations, and intended to submit the data and results parts in *Technological Forecasting & Social Change*). This section highlights the roles of perceived usefulness, social image, perceived well-being, privacy concerns, and types of personalities (Article 5; section 2.4.2.)

As mentioned in the literature review in our general introduction, conceptual issues about technology acceptance models are pointed out by researchers. Consumer behavior theory provides evidence that only functional benefits are not sufficient to explain consumer attitudes (Benbasat & Barki, 2007; Chitturi et al., 2008; Christodoulides & Michaelidou, 2010; Chuttur, 2009). Consequently, some antecedents are not sufficiently investigated in the literature, such as perceived well-being (Chitturi et al., 2008), social image (Bagozzi,

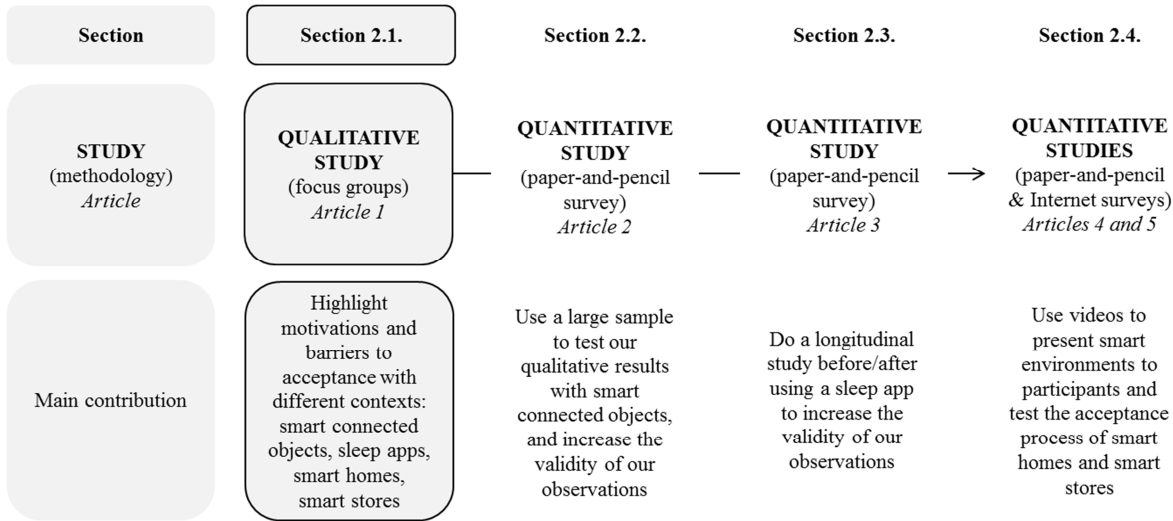
2007; Venkatesh & Davis, 2000), or privacy concerns (Hong & Thong, 2013). Table 5 describes a summary of our studies in chapter 2, the antecedents of adoption chosen and the targeted research gaps from the literature.

Contexts of study	Antecedents of adoption	Targeted research gaps
<p>Section 2.1.: SCO, smart apps, smart homes, smart stores (N = 40; 4 focus groups) (<i>Article 1</i>)</p> <p>Section 2.2.: SCO (N = 702) (<i>Article 2</i>)</p> <p>Section 2.3.: Sleep app (N = 182; longitudinal study) (<i>Article 3</i>)</p> <p>Section 2.4.: 1. Smart homes (N = 342) (<i>Article 4</i>); 2. Smart stores (N = 409) (<i>Article 5</i>)</p>	<p>Perceived usefulness (PU): degree to which people believe that using an IoT technology enhances their performance (e.g., Davis, 1989) (<i>Articles 1, 2 and 3</i>)</p> <p>Perceived ease of use (PEU): degree to which people believe that using an IoT technology is easy to use and free of efforts (e.g., Davis, 1989) (<i>Articles 1, 2 and 3</i>)</p> <p>Perceived well-being: a desired state of objective and subjective well-being involved in the various stages of the consumer/product life cycle in relation to IoT technologies (e.g., Sirgy & Lee, 2004) (<i>Articles 1, 2, 3 and 4</i>)</p> <p>Perceived social image (PSI): degree to which using an IoT technology enhances a social status and image within a social group (e.g., Venkatesh & Davis, 2000) (<i>Articles 1, 2 and 4</i>)</p> <p>Privacy concerns: to which extent users are concerned about the flow of their information through IoT technologies (e.g., Phelps et al., 2000) (<i>Articles 1, 2, 3 and 4</i>)</p>	<ul style="list-style-type: none"> - Study adoption and rejection antecedents of technology usage (Davis et al., 1989; Mathieson, 1991; Rogers, 1962) (<i>Articles 1, 2, 3 and 4</i>) - Study individual characteristics (e.g., Bagozzi, 2007; Venkatesh et al., 2012; Rogers, 1962) (<i>Articles 1, 2, 3 and 4</i>) - Study affective and cognitive factors (e.g., Ajzen & Fishbein, 2005; Triandis, 1980) (<i>Articles 1, 2, 3 and 4</i>) - Study the role of emotions (e.g., Myers, 2010; Sniehotta, 2009; Venkatesh et al., 2012) (<i>Articles 3, 4 and 7</i>) - Study social factors (Beaudry & Pinsonneault, 2010; Venkatesh & Bala, 2008) (<i>Articles 1, 2 and 4</i>) - Study enjoyment and hedonism (Davis et al., 1992; Venkatesh et al., 2012) (<i>Articles 1, 2, 3 and 4</i>) - Adapt the TAM to a new context (Taylor & Todd, 1995) (<i>Articles 2 and 3</i>) - Improve external validity with various contexts and technologies

Contexts of study	Antecedents of adoption	Targeted research gaps
	<p>Quantified-self: the ability to collect the data and manage health indicators with IoT technologies to improve, among others, self-knowledge, health, and performances (e.g., Kozinets, 2012) (<i>Article 3</i>)</p> <p>Innovativeness: the degree of tendency and willingness to adopt IoT technologies more quickly than other consumers (e.g., Midgley & Dowling, 1978) (<i>Articles 1, 2, 3 and 4</i>)</p> <p>Personalities:</p> <ul style="list-style-type: none"> - Well-being personality: people more or less predisposed to recognize, accept, feel and share senses of perceived well-being (e.g., Csíkszentmihályi, 1975; Olson, 1999; Mill, 1998) (<i>Articles 1, 3 and 4</i>) - Empowered personality: people predisposed to get, feel, then use senses of power with a willingness to do quantified-self (e.g., Harris & Westin, 1991; Kozinets, 2012; Mill, 1998; Olson, 1999) (<i>Articles 1, 3 and 4</i>) 	<p>(e.g., Moore & Benbasat, 1991; Sniehotta, 2009; Thomson et al., 1991) (<i>Chapters 2 and 3</i>)</p> <ul style="list-style-type: none"> - Adapt technology adoption theory to a consumer context (e.g., Beaudry & Pinsonneault, 2010; Curran & Meuter, 2005; Scherer & Craddock, 2002), and to the French market (e.g., Scherer & Craddock, 2002) (<i>Articles 1, 2, 3 and 4</i>) - Measure constructs with more than two items (e.g., Venkatesh & Davis, 2000) (<i>Articles 2, 3 and 4</i>) - Use structural equation modelling to analyze the data (e.g., Venkatesh & Davis, 2000) (<i>Articles 2, 3, and 4</i>) - Conduct longitudinal studies (Beaudry & Pinsonneault, 2010) (<i>Article 3</i>) - Highlight managerial recommendations (e.g., Chuttur, 2009) (<i>Articles 1, 2, 3 and 4</i>)

Table 5: The IoT antecedents studied in this thesis and the targeted gaps from literature

Table 5 indicates that this thesis aims to improve external validity with various consumer contexts and IoT technologies/environments, and to respond to different actual research gaps by notably combining mixed methodologies (e.g., qualitative and quantitative) and relevant antecedents (e.g., perceived usefulness, perceived ease of use, perceived well-being, perceived social image, privacy concerns, quantified-self, innovativeness, personalities). Variables from the TAM (Technology Acceptance Model; Davis, 1989), TPB (Theory of Planned Behaviour; Ajzen, 1985), TRA (Theory of Reasoned Action; Fishbein, 1967) or UTAUT 1 (Unified Theory of Acceptance and Use of Technology; Venkatesh et al., 2003) tend to be reused in the literature from one theory to another. Thus, technology antecedents vary, extended models are created, and no theoretical model has been established to explain the acceptance of the IoT yet (Verhoef et al., 2017). Therefore, our articles developed in chapter 2 show consumers' perceptions about IoT technologies, with SCO, smart apps, and smart environments. In section 2.1., we present a preliminary qualitative study about our topics (SCO, sleep apps, smart homes, smart stores). This article highlights motivations and barriers to acceptance thanks to four focus groups.



2.1. IoT and smart technologies acceptance: An exploratory qualitative analysis of the IoT technology acceptance: the roles of technology and self-improvement benefits, perceived risks, and user personalities (Article 1)

Abstract

The Internet of Things (IoT) and smart connected objects (SCO) are invading consumers’ lives. Research has shown the importance of further investigating and understanding the IoT’s acceptance, which is a highly under-investigated domain (Verhoef et al., 2017). This study contributes to the literature with four qualitative studies about SCO (study 1), smart apps (study 2), and smart environments (study 3). This allows us to highlight the roles of antecedents like perceived well-being, perceived social image, privacy concerns and personalities, but also of the technology acceptance model’s (TAM; Davis, 1989) main variables (e.g., perceived usefulness, perceived ease of use). The data comes from four focus groups with ten participants in each. Our interpretation of the qualitative information obtained leads us to (1) classify the IoT antecedents into four categories: technology benefits, self-improvement benefits, perceived risks and fears, and personality traits; (2) create a system of values of the IoT acceptance with four values: privacy, well-being, social, and utility; (3) define the importance of each antecedent according to the probability of adoption of SCO.

Figure 8 sums up our main objectives and methodology for Article 1:

<p>Article 1</p>	<p>OBJECTIVES</p>	<ul style="list-style-type: none"> - Answer to calls for research (Foroudi et al., 2018; Oh et al., 2007; Verhoef et al., 2017) - Highlight the roles of antecedents: the TAM’s main variables (e.g., perceived usefulness (PU), and perceived ease of use (PEU)), perceived well-being, perceived social image, privacy concerns and personalities - Classify these antecedents into four categories: technology benefits (e.g., PU, PEU), self-improvement benefits (e.g., well-being, social value), perceived risks and fears (e.g., privacy concerns, health concerns), and personality traits (e.g., innovativeness, well-being and empowered personalities) 	
<p>METHODOLOGY</p>	<p>QUALITATIVE STUDIES: FOCUS GROUPS (N=10)</p>		
	<p>Smart connected objects</p>	<p>Smart sleep apps</p>	<p>Smart environments</p>
	<p>May 2015</p>	<p>October 2016</p>	<p>September 2017</p>
<p>PUBLICATIONS</p>	<p>Attié, E., & Meyer-Waarden, L. (2016). The IoT, generating new behaviors and consumer needs? Journée Toulousaine du Marketing (TSM), Toulouse, France</p> <p>Attié, E., & Meyer-Waarden, L. (2015). A theoretical model incorporating social influence of the Internet of Things. Research symposium on smart connected objects (IESEG), Paris Nanterre, France</p> <p><i>Targeted journal: Journal of Marketing Management</i></p>		

Figure 8: Main objectives and methodology (Article 1; qualitative research)

2.1.1. Introduction

The IoT and smart technologies started to invade the French market in 2005 with Nabaztag — then renamed Karotz— becoming the first French smart connected object (SCO). But it was with the launch of the first Apple Watch in April 2015 that consumers became more informed about the new phenomenon through advertising and word-of-mouth. This first study related to the phenomenon started in 2015 when SCO were still trying to penetrate the French consumer market. This study found that only half of the people surveyed knew what a SCO was, aside from a smartphone. Moreover, three out of ten people interviewed did not intend to try any SCO. Reluctance toward SCO seemed greater than it is now in 2019. Figure 9 shows the increase of number of SCO by person from 2003 to 2020 forecasts —worldwide numbers.

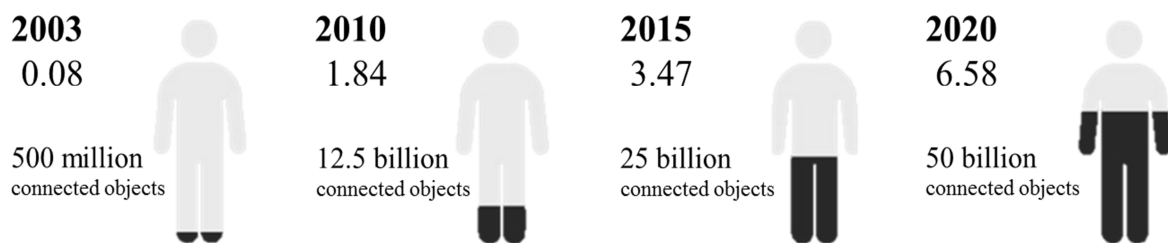


Figure 9: Number of smart connected objects per person (Cisco, 2017)

Furthermore, the first marketing peer-to-peer reviewed article about the IoT was published in 2010, and then 13 others came after 2015, showing a growing interest among academics in the marketing field. In contrast, in other fields, such as medicine, engineering and law, 134 papers on the IoT have been published since 2002. Marketing researchers have sent many calls for research, highlighting the need to understand consumer acceptance and the influence of IoT technologies on consumers' behavior and perceptions (Foroudi et al., 2018; Oh et al., 2007; Verhoef et al., 2017).

Research on technology acceptance brings out different antecedents and none has defined relevant antecedents for the IoT yet (Verhoef et al., 2017). Therefore, this exploratory qualitative study aims to provide the directions and variables to study the acceptance of IoT technologies that are still underdeveloped.

This qualitative research presents three studies. The first qualitative study, about SCO, was carried out in May 2015; the second study, about smart apps, in October 2016; and the third and last study, about smart environments, in September 2017. Having qualitative studies

about different smart technologies that were carried out in three consecutive years allows us to compare the evolution of perceptions according to technologies, time, advertising, and a changing market.

This article is organized in the following manner: after presenting the data and methodology in section 2.1.2., section 2.1.3. shows the results, and section 2.1.4. highlights the discussion of these results. In section 2.1.5., the contributions are discussed, and finally, the main conclusions, limits and future research directions are highlighted in section 2.1.6.

2.1.2. Methodology

To define the antecedents of the IoT acceptance, we use the group nominal technique (i.e., a structured method for group brainstorming that encourages contributions from everyone and facilitates quick agreement on the relative importance of issues, problems, or solutions; Claxton et al., 1980; Delbecq & Van de Ven, 1971; Giannelloni & Vernetto, 2001). This method allows a better understanding of the perceptions of new or existent products and services as well as consumer behavior and demand (Vernetto, 2011). Moreover, it allows us to structure and to classify qualitative information about existing or new products and services (Giannelloni & Vernetto, 2001).

2.1.2.1. Interviews guide and procedure

Before the brainstorming session, participants who volunteered to participate to our studies receive an email informing them of the session's subject (e.g., motivations and barriers toward SCO) and some ideas for discussion (e.g., personal/technology/routine benefits and risks) (see Appendix 2A). During the session, we first remind them of the topic, then a warm-up of five minutes is done with a daily life problem not linked to the context of study (e.g., subjects: tips to review midterms, travelling alone vs. with friends, ghosting people on social networks), then each person gives one idea about the subject and we combine all their ideas. The process lasts between half an hour and one hour, and each session involves three individual activities and three group activities for each study (e.g., study 1 with smart objects, study 2 with smart apps, and study 3 with smart environments). Table 6 describes the methodology used.

Step	Process
1	Individual time. SCO (experimentation 1), smart apps (experimentation 2) and smart environments (experimentation 3) are defined. A scenario is given (Appendix 2B). Respondents write what they think about SCO or smart apps or smart environments according to the focus group, the positive and negative points, and their questions.
2	Group discussion time. Each respondent says what (s)he has previously written and everything is put on a board so that everyone can see it. Sometimes, respondents explain with more details their ideas so that everyone understands everything.
3	Group discussion time. Respondents clarify their ideas to categorize them into groups (Appendix 2C).
4	Individual time. Respondents select the ideas that seem the most important to them and write their thoughts, the positive and negative points, and other questions.
5	Group discussion time. Respondents say what they have written and discuss together their points of view. Ideas that do not seem to belong to any group are deleted.
6	Individual time. Respondents evaluate the importance of each idea from 1 (strongly disagree) to 5 (strongly agree) to define average scores of importance for each idea (Appendix 2D).

Table 6: The session process of the group nominal technique

2.1.2.2. Samples

Eight to ten participants is the recommended sample size to ensure dynamism and better interactions (Vernette, 2011). For each study, 10 respondents talked about their perceptions regarding the IoT and smart technologies. They are non-users and users, and some work in the IoT field, allowing us to obtain different visions and attitudes. Age and gender should have no significant effect on the results (Vernette, 2001). Characteristics of these samples are reported in Table 7.

Context of study	SCO	Smart apps	Smart environments
Number of participants	10	10	10 for smart homes 10 for smart stores
Gender	50% women 50% men	60% women 40% men	60% men 40% women
User status	40% non-users 60% users	30% non-users 70% users	50% non-users 50% users
Job	40% students 60% full-time job (50% work in the IoT industry)	100% students	100% students

Table 7: The characteristics of the group nominal technique samples

2.1.2.3. Data analysis

The main ideas are organized into groups, following the group nominal technique of data analysis (Claxton et al., 1980; Delbecq & Van de Ven, 1971; Giannelloni & Vernetto, 2001). Furthermore, the average scores of importance for each idea (\bar{X}_i) show which antecedents seem to be the most important ones for actual and potential users (Appendix 2D).

$$\bar{X}_i = \frac{\sum x_{ij}}{n}$$

\bar{X}_i = mean of the average score of the idea i

x_{ij} = score of each participant j for each idea i

n = number of participants

2.1.3. Results

The data analysis highlights the main variables that influence consumers' beliefs about the different IoT contexts and consequently their impacts on the IoT and smart technologies adoption. Table 8 shows the classification of the ideas with a short explanation for each idea. Details of the categorization are available in Appendix 2C.

Utility value
Participants mainly give advantages about using SCO (e.g., exchanging information, getting news, tracking sport performances, etc.). Moreover, some non-users have a more negative idea of how SCO work, finding them harder to use and a challenge to deal with.
Perceived well-being
Participants mention the ideas of playing, having fun, taking care of themselves, and feeling positive. Stress can be increased through fears regarding the IoT and smart technologies. More precisely, health risks linked to addiction consequences, the influence of electromagnetic radiations on people, which is still unknown, privacy concerns or risks of hacking are sources of potential doubts and stress.
Social value
Social influence comes from external sources close to people (e.g., family, friends, work), linked to social places (e.g., a neighborhood) or to marketing and advertising (all participants). Only very few participants think that smart environments will improve their relationships; most participants believe such environments will decrease their social interactions.
Privacy concerns
The main barrier to the acceptance of the IoT and smart technologies seems to be about privacy concerns. Non-users seem more afraid of confidentiality and surveillance issues than users. One way to decrease this negative perception would be transparency about the way the data is collected, stored, and used.

Personality traits and characteristics

Innovativeness

Some participants show signs of technology curiosity and optimism when talking about the IoT and smart technologies.

Well-being personality

We perceive that some participants seem to be more or less predisposed to feel, accept, and share feelings of well-being than others. They are more interested by IoT technologies giving either short- or long-term entertainment and feelings of hedonism, while improving health.

Empowered personality

Some users also seem to be more or less predisposed to get, feel, then use their senses of power over themselves with a willingness to do quantified-self through self-tracking, self-knowledge and self-management. Also, low-empowered users seem to be reassured with a very high ethical value.

Table 8: Summary of qualitative findings

This qualitative study builds on prior research to enhance the understanding of which antecedents drive willingness or reluctance to accept the IoT. Table 8 shows that several criteria are mentioned by the participants. The utility value seems to be important for non-users, so our findings suggest useful and easy-to-use benefits will attract potential users. For users, well-being and social benefits are more important than the utility value and represent the motivations to continue using the IoT and smart technologies. Privacy concerns are the main barrier to the confidence toward the technology and its use. However, these concerns are moderated by the experience of use (i.e., non-users are more worried than actual users) and by the personality traits of consumers (i.e., innovative, high well-being, and empowered personalities are more attracted to these technologies and less concerned about privacy). Table 9 classifies the importance of the antecedents according to the IoT and technology and contexts, with 1 = most important antecedent.

Physical objects	Mobile apps	Smart environments	
Smart/connected objects	Sleep apps	Smart homes	Smart stores
Well-being (1)	Well-being (1)	Well-being (1)	Well-being (1)
Privacy concerns (1)	Privacy concerns (1)	Privacy concerns (1)	Privacy concerns (1)
Social value (2)	PU (2)	Utility value (2)	Utility value (2)
PU (3)	PEU use (3)		Social value (3)
PEU (4)			

PU stands for perceived usefulness; PEU for perceived ease of use.

Table 9: Importance of antecedents according to IoT technologies and environments

Table 9 shows that no matter the IoT technology and context, well-being remains the most important antecedent, and privacy concerns, the second antecedent. Regarding smart objects, social image and influence is the third most important antecedent, followed by perceived usefulness (PU) and perceived ease of use (PEU). With sleep apps and smart homes, social image and influence does not appear to be significant, and only the utility value has an influence. Finally, regarding smart stores, utility value is the third most important antecedent, followed by the social image. We classify the antecedents found in this research into four main categories: technology benefits (e.g., PU, PEU), self-improvement benefits (e.g., well-being, social value), perceived risks and fears (e.g., privacy concerns, health concerns), as well as personality traits (e.g., innovativeness, well-being personality, empowered/controlling personality). Figure 10 sums up these results.

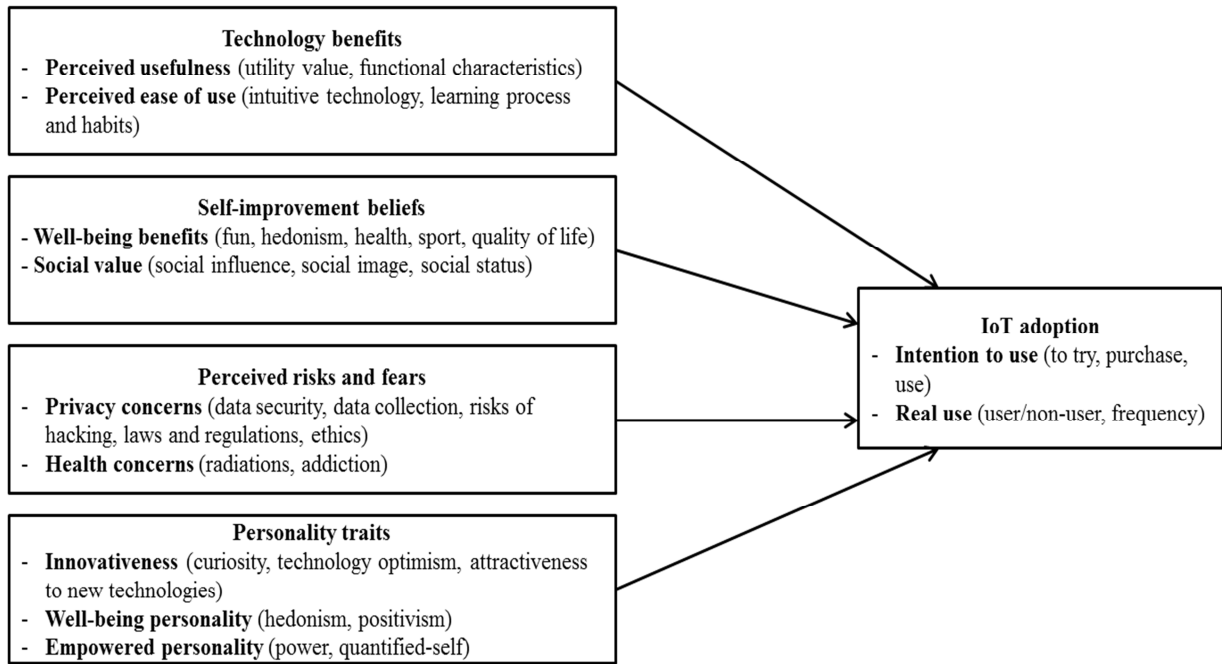


Figure 10: The main antecedents of IoT acceptance

Moreover, the average scores of importance (Appendix 2D) show which antecedents seem to be the most important and how they influence the probability of individuals adopting the IoT and smart technologies. Figure 11 shows the importance of the antecedents of the IoT and smart technologies acceptance according to the probability of adoption.

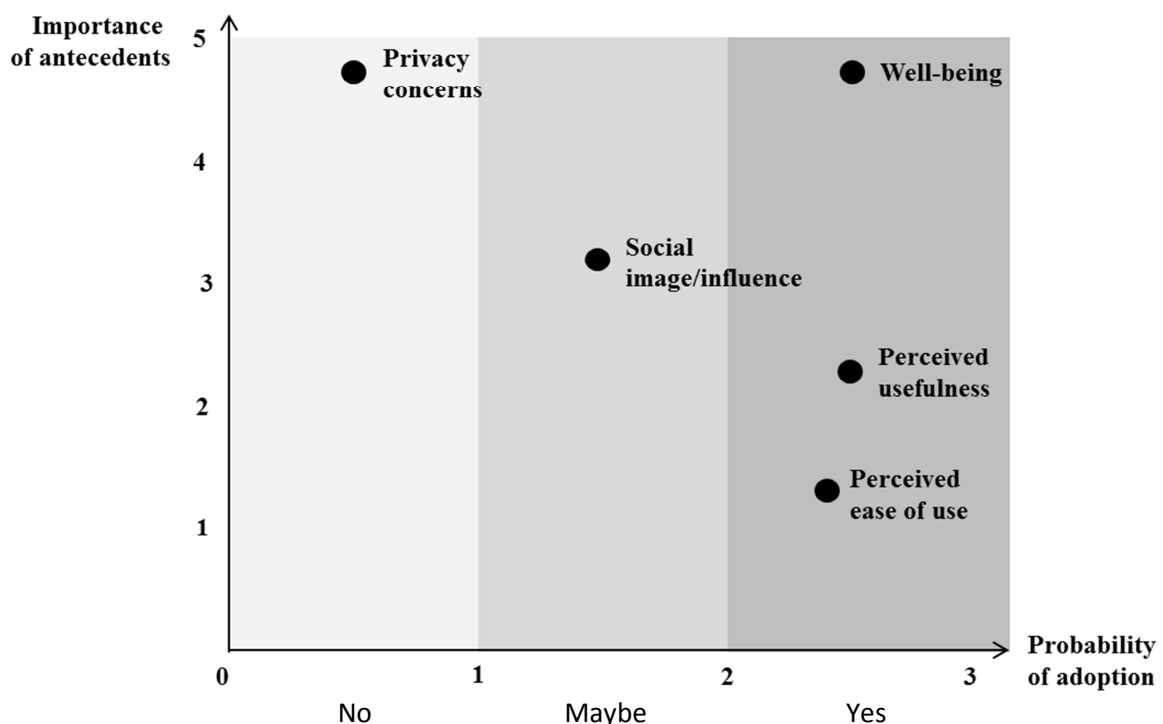


Figure 11: The importance of antecedents according to the probability of adoption

Privacy concerns and well-being are the most important antecedents of the IoT and smart technologies acceptance. However, if consumers believe that the IoT can improve their well-being, they are more likely to adopt this technology, diminishing privacy concerns. Perceived social image also plays an important role in the acceptance process. The traditional TAM variables, perceived usefulness and perceived ease of use, increase the probability of accepting the IoT but seem to be less important over time. Research has shown that PU and PEU are strong determinants of technology adoption (Calantone et al., 2006; Davis, 1989; King & He, 2006; Taylor & Todd, 1995; Venkatesh & Davis, 2000). Moreover, early adopters are more attracted to technology basic functions than middle or late adopters because other antecedents of usage become more important (Chau & Hu, 2001; Huh & Kim, 2008; Muk & Chung, 2005; Townsend et al., 2001). These findings follow the theory of Herzberg (1959), which shows that people are led by two kinds of antecedents: satisfaction through primary needs and motivation through self-improvement benefits. In the context of the IoT and smart objects, satisfaction seems to come from the technology benefits, through high PU and PEU, and motivation to use seems to come from self-improvement benefits, through well-being, social benefits, and privacy.

Furthermore, these findings and our observations lead us to build a system of values defining the antecedents of IoT and smart technologies (Figure 12). Privacy concerns seem to be the basis of acceptance or rejection. Then, according to each consumer, well-being, social, and/or utility values influence the acceptance process.

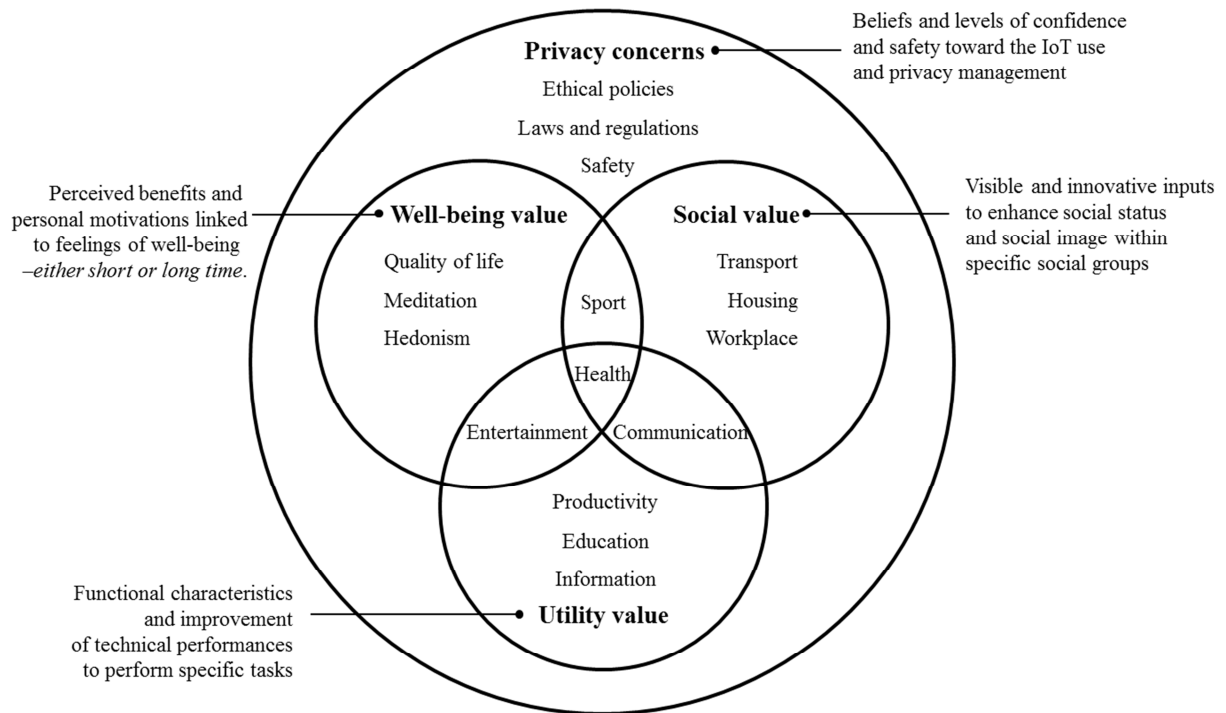


Figure 12: The system of values of the IoT acceptance and components

Figure 12 shows that the basis of privacy concerns includes the well-being value, the social value, and the utility value, so if people perceive high privacy concerns, they will also perceive lower well-being, social, and utility values. We define each value below:

1. **Privacy concerns:** Privacy concerns are the basis of the acceptance values of the IoT. Without trust, consumers tend to reject the technology, regardless of the other perceived benefits. Privacy concerns are personal beliefs and levels of confidence toward the IoT use and privacy management (Phelps et al., 2000). These concerns mainly come from personal experiences and/or social influence. Privacy concerns show the confidence or anxiety felt about the safety of using the IoT and the extent to which the user could rely on the IoT (Chaudhuri & Holbrook, 2001; Shin, 2010).
2. **Utility value:** Utility value is a primary functional characteristic given by the IoT and improves technical performances while using the IoT and smart technologies. The IoT can be seen as a way of doing something useful, like improving productivity and communication. This determines to what extent the IoT and smart technologies fit into daily routines, thanks to primary needs benefits (e.g., Strahilevitz & Myers, 1998).

3. Well-being value: The IoT promises well-being benefits (Porter & Heppelmann, 2014). Well-being is defined as a positive feeling coming from hedonistic inputs and/or personal satisfaction (Van der Heijden, 2004). Most of the time, it is linked to good quality of life and health: well-being includes choices and activities aimed at improving physical and mental health, and social satisfaction (Naci & Ioannidis, 2015). This feeling of well-being can be punctual (e.g., directly linked to an entertainment or to good news and therefore a hedonic contribution that has a beginning and an end, such as enjoyment, hedonism, and positive experiences; e.g., Van der Heijden, 2004), or of a more constant nature (e.g., a daily habit learned and reproduced, leading to a healthier lifestyle and better quality of life).

4. Social value: Social value is defined as visible and perceived innovative inputs used to enhance social status and image within specific social groups (e.g., Moore & Benbasat, 1991). Users can be influenced by social groups, such as family members, friends, neighbors, and colleagues, as well as by socio-professional categories, such as the media and advertising, when deciding to use, or not use, new technologies. If some users are not easily influenced by their social entourage, the privacy, well-being, and/or utility values will take precedence over the social value, and the IoT and smart technologies will then be used in private.

These values influence consumers' beliefs and opinions, as well as the acceptance and use of the IoT and smart technologies. There might be common points or overlaps between each value. For example, the well-being and social values have in common sports activities to improve both well-being and social values (e.g., using a sport wristband is visible and gives a certain image to the user, while it can also help improve health).

2.1.4. Discussion

These results highlight four main antecedents of the IoT and smart technologies, namely technology benefits, self-improvement benefits, privacy benefits, and personality traits. Each category has more or less importance for favoring the adoption. This discussion makes the link between our findings and the literature.

2.1.4.1. Technology benefits

The traditional TAM variables, namely perceived usefulness (PU) and perceived ease of use (PEU) seem to be important antecedents of IoT adoption. In the literature, they are the variables most used to explain technology adoption (Hauser & Simmie, 1981) and strong determinants of technology usage (Calantone et al., 2006; Davis, 1989; Taylor & Todd, 1995). Therefore, studying the TAM (Davis, 1989) seems to be the common-sense approach to studying the adoption of the IoT and smart technologies, as it is still one of the most influential theories of human behavior (King & He, 2006; Venkatesh et al., 2003). Meta-analyses on the TAM show a robust, significant, and powerful model with strong psychometric properties that can be used within various technology contexts (King & He, 2006; Lederer et al., 2000; Legris et al., 2003). However, PU and PEU are criticized for their low predictive power and limitations regarding theories of consumer behavior in marketing (Bagozzi, 2007; Chuttur, 2009; Franz & Robey, 1986; Hu et al., 1999; Pikkarainen et al., 2004; Wu & Wang, 2005). It also seems that PU and PEU are more important to non-users and new users. The literature shows that there is a decrease in the influence of PU and PEU over time of use, but that both are reasons to accept smart technologies (Venkatesh et al., 2003). However, other important cognitive and social antecedents of new technology adoption and usage should also be studied (Benbasat & Barki, 2007; Chuttur, 2009), such as hedonic benefits (Chitturi et al., 2008; Sirgy, 2012) and social influence (Bagozzi, 2007; Venkatesh & Davis, 2000).

2.1.4.2. Self-improvement and well-being benefits

When talking about the IoT and smart technologies, users also mention well-being expectations. People want to live happily and they want to feel good about their choices and habits (Seligman, 2011). Hedonic motives thus appear to be relevant antecedents of technology adoption in consumer contexts (Bruner & Kumar, 2005; Childers et al., 2001; Dabholkar & Bagozzi, 2002; Hirschman & Holbrook, 1982; Kim & Forsythe, 2008; Kulviwat et al., 2007; Van der Heijden, 2004). Researchers recognize the importance of studying consumer well-being (Su et al., 2014).

Furthermore, some people, mostly non-users, mention the social factor as either a motivation (e.g., being included in a social group) or a barrier (e.g., not doing like others) to the adoption of the IoT and smart technologies. This follows the Social Cognitive Theory which shows that social image impacts technology adoption (Bandura, 1986; Compeau & Higgins, 1995). Indeed, using an innovation can give a positive social image to users and improve acceptance as well as associated positive feelings (Kuisma et al., 2007; Rogers, 1983). Therefore, consumers who perceive a new technology as conforming socially are more likely to use it and adoption becomes a social process (Hellström, 2004).

2.1.4.3. Perceived risks and fears

Consumers have their own personal beliefs, coming from personal experiences and/or social influence. This explains an individual consumer's confidence or anxiety about safety of using the IoT and the extent to which the user feels s/he can rely on the technology (e.g., Chaudhuri & Holbrook, 2001; Shin, 2010). The way the IoT tracks and collects personal data for personalization is intrusive, arousing privacy concerns (Awad & Krishnan, 2006; Hong & Thong, 2013; Phelps et al., 2001). Fear influences consumers' privacy expectations (e.g., Beitelspacher et al., 2012) and the rejection of the IoT mostly comes from privacy concerns. When users perceive risks regarding the way their data is used by technology, they tend to develop feelings of stress linked to a lack of control, and this subsequently decreases their feelings of well-being (Van der Heijden, 2004; Wuenderlich et al., 2015) that can lead to the rejection of the technology (Lynch & Ariely, 2000). However, there is no increase of stress if the benefits of personalization are higher than the loss of privacy (Xu et al., 2011). Another perceived threat relates to the health risks associated with, for example, the accumulation of low-level radiation which have an unknown effect on risks of illnesses like cancers (Myung et

al., 2009), signs of addiction, and physical dangers related with technical problems. Governments are starting to consider these issues and are developing regulations, laws, and prevention campaigns concerning the IoT risks.

2.1.4.4. Personality traits

Some users are more attracted to the IoT and smart technologies than others, pointing out different personality traits. It appears to be important to consider personalities when studying technology adoption, as each consumer is different and thus their perceptions differ as well. According to the Innovation Diffusion Theory, people may react differently to new products due to personality traits, such as innovativeness (Rogers, 1983). Research has also shown that technology optimism facilitates innovation adoption (Gilly et al., 2012). Innovative people have more positive beliefs about technology use than non-innovative ones (Agarwal & Karahanna, 2000; Eastlick & Lotz, 1999; Goswami & Chandra, 2013; Reynolds & Ruiz De Maya, 2013). Moreover, some users seem more optimistic, positive, and willing to feel and to look for well-being than others. Personalities refer to the way people interact and respond to their environment (Olson, 1999). Csíkszentmihályi (1975) defines autotelic people as individuals with emotional intelligence and who readily express their feelings. These consumers should use technology as a way to experience well-being (Seligman, 2011). Low well-being people can use SCO to communicate and decrease their emotional loneliness and increase self-esteem (Hoffman, 2012; House et al., 1988; Kawachi and Berkman, 2001). Other users favor utility benefits rather than hedonism when making choices (Harris & Westin, 1991). These empowered participants seem to be more in control (e.g., of the discussion, of their lives, of their opinions) than others: high-empowered people tend to be self-confident, rather rational, and wise (Hock, 1962; Zeanah & Fox, 2004). Thus, empowered people favour utility benefits rather than hedonism when making choices (Harris & Westin, 1991) to take control of their lives (e.g., Cases, 2017). They are more informed and actor of their daily life (e.g., Cases, 2017). Low empowered consumers own a natural prudence and inform themselves before accepting new products (e.g., Mill, 2012), so the acceptance process might be longer. A minority of people have all the characteristics of a particular type (Zeanah & Fox, 2004).

2.1.5. Contributions

The main goal of this research is to highlight relevant antecedents of the IoT acceptance. This qualitative study allows us to define important motivations and barriers to the IoT acceptance from both non-users and users. This study aims to make three kinds of contributions to the field: theoretical, methodological, and managerial contributions. We define these below.

2.1.5.1. Theoretical contributions

The first contribution of this qualitative research is to enhance the antecedents of the adoption and usage of the IoT and smart technologies, as suggested by Verhoef et al. (2017). We confirm that TAM's main variables (e.g., PU, PEU) are relevant in the IoT context, regardless of the technology (e.g., Calantone et al., 2006; Davis, 1989; Taylor & Todd, 1995), even if the literature states that the TAM is not adapted for new or hedonic technologies (Benbasat & Barki, 2007); this supports the finding that IoT technologies are perceived as useful technologies and not hedonic technologies before use. Furthermore, this research shows the important role of well-being when studying the adoption of the IoT and smart technologies, as users believe that the IoT can improve their well-being. This is in line with literature (e.g., Atzori et al., 2010; Etzioni, 1999; Harkin et al., 2016; Kluger & DeNisi, 1996; Porter & Heppelmann, 2014; Xia et al., 2012), although this concept of well-being needs to be further developed (Anderson et al., 2013; Wunderlich et al., 2015).

Moreover, the role of social value is mitigated and seems to depend on the technology—less important for smart apps, but more important when the technology is visible to others—(Kuisma et al., 2007). This is in line with Triandis' theory (1971), which adds a social variable to better understand behaviors toward technology (Milhausen et al., 2006).

Finally, this research points out the important role of privacy issues. They appear to be the main obstacles to using the IoT and smart technologies (e.g., Buchanan & Ess, 2006; Hong & Thong, 2013), even though privacy concerns decrease with experience of use. This is in line with the privacy-personalization paradox: even if users have privacy concerns, they still intend to use technologies if they perceive higher benefits of personalization (Dimitriadis & Kyrezis, 2010; Sirdeshmukh et al., 2002).

2.1.5.2. Methodological contributions

This study has reproduced four qualitative studies: one for smart objects, one for smart apps, one for smart homes, and one for smart stores. The reproduction of the same methodology over the years but with a different IoT context enables us to increase the external validity of the results, with different contexts and times of study.

2.1.5.3. Managerial contributions

The first managerial contribution of this study is to highlight antecedents of acceptance and adoption of the IoT and smart technologies. This should help companies to better know the main motivations and barriers of using these smart technologies. We show the roles of well-being value, social value, perceived usefulness, perceived ease of use, and privacy concerns, according to IoT contexts.

Second, the system of perceived values of the IoT can be used by managers to refine their marketing strategies, and products and services development.

Finally, this research categorizes types of IoT users according to their personalities (e.g., well-being and empowered personalities). This should help managers to refine their targeting strategies.

2.1.6. Limits and further research directions

The research is not free from limitations and leaves room for improvement and thus further research.

The first limit is linked to the small sample size and its type. All participants are from France and most of them are from the Y and X generations, making it hard to generalize the results. A future research project could replicate this study with respondents from all generations and from other countries (Straub et al., 1997).

The second limit is that we interpret the results ourselves and interpretation can differ according to researchers (Verneette, 2011). In the future, researchers should replicate this study by using the same methodology. The discussion groups are also conducted in French and this adds a vocabulary interpretation when it comes to translating the findings into English. It is

also recommended to deepen these findings with quantitative studies to build theoretical models (e.g., Venkatesh & Davis, 2000).

The third limit is that no real-time consumer behavior indicators are used, and perceptions can differ according to people and reality (e.g., Ahmadpour et al., 2016; Donaldson & Dunfee, 1994). Moreover, during the discussion participants could see each other, removing confidentiality and anonymity from our research and perhaps influencing some participants' responses in light of the judgement they felt from others. Therefore, it is recommended to collaborate with companies of smart objects in order to get real-time data (e.g., Ahmadpour et al., 2016; Van Ittersum et al., 2013).

Finally, consideration should be taken of new laws, changing demand, media alerts, and social influences that may influence people's beliefs and consequently the image of the IoT, and could ultimately have an effect on the antecedents highlighted in this research.

Summary of contributions

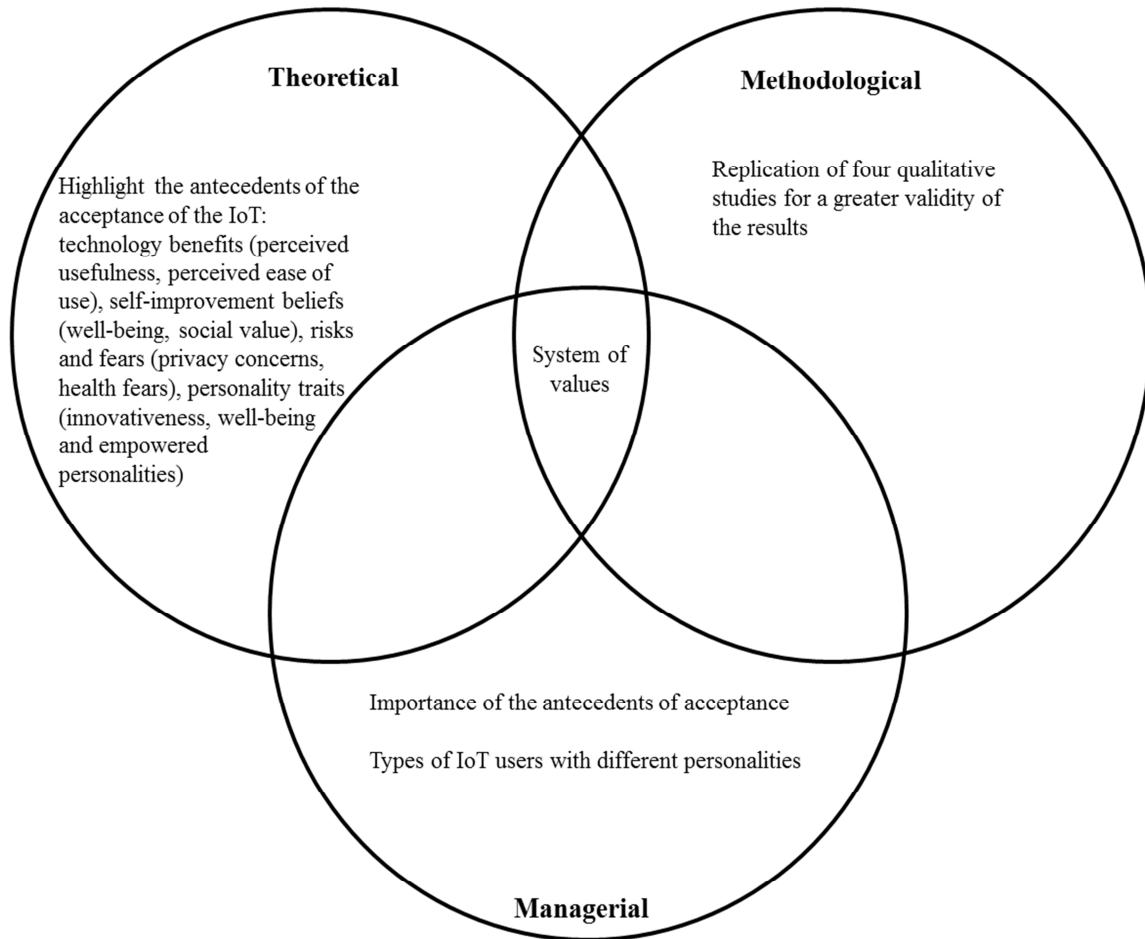


Figure 13: Summary of contributions (*Article 1; qualitative research*)

Figure 13 shows that we make three main contributions:

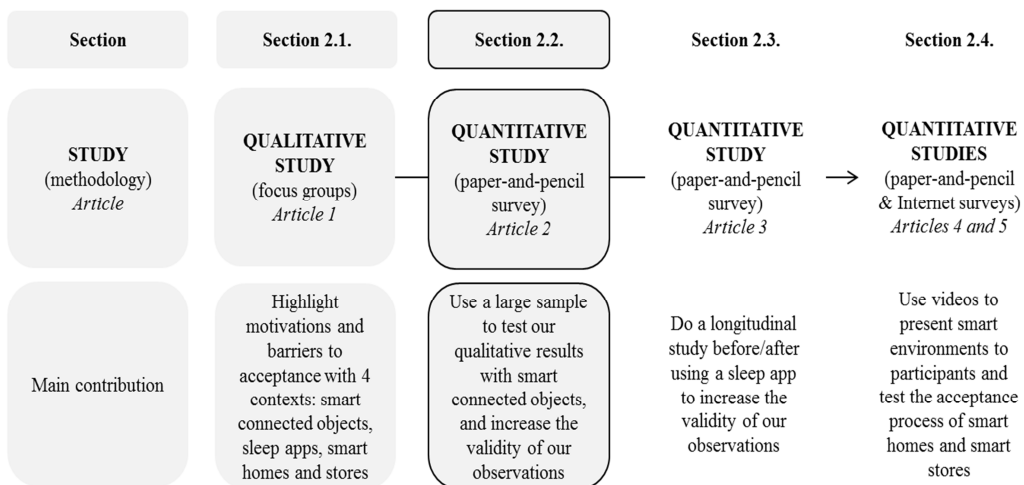
- (1) Theoretical contributions: we highlight the roles of antecedents of the IoT and smart technologies acceptance: TAM's main variables (i.e., PU, PEU), well-being, social influence, privacy concerns, and different kinds of personalities;
- (2) Methodological contributions: we reproduce the same methodology with four different contexts to maximize the generality and understanding of the results;
- (3) Managerial contributions: we show the importance of different antecedents, and how to recognize types of consumers and potential targets in order to improve the acceptance process of the IoT technology.

Transition: from qualitative to quantitative studies

This qualitative research enables us to deepen our knowledge of the motivations and obstacles regarding the acceptance of the IoT and smart technologies. However, as we stated before, the quality of the data is highly subjective. The small sample size with qualitative research makes it hard to generalize the results. Also, the data validity is hard to assess and the interpretation of the results could differ according to researchers, even with the same participants and the same information (Verette, 2011). Our first qualitative research shows that the TAM's main variables (PU, PEU, intention to use, real use), perceived well-being, social image, privacy concerns, and personality traits are relevant antecedents of acceptance. The aim of the next studies is to increase the accuracy, relevance and validity of these findings by using statistics such as conceptual models and structural equation modelling. Therefore, a follow-up with a larger quantitative sample is done and presented in the next sections with:

- Article 2: A theoretical model incorporating social influence and cognitive processes to explain the adoption of the Internet of Things and smart connected objects (Section 2.2.)
- Article 3: A longitudinal study to explain the adoption of sleep apps with the TAM, perceived well-being, quantified-self, privacy concerns and different types of personalities (Section 2.3.)
- Article 4: The acceptance process of the Internet of Things: How to improve the acceptance of the IoT technology? (Section 2.4.1.)
- Article 5: Consumers' acceptance and resistance factors toward smart connected stores (Section 2.4.2.)

In section 2.2., we present a quantitative study about the acceptance of SCO over three years of data collection, in order to test our qualitative results regarding the adoption of SCO.



2.2. Smart objects acceptance and adoption: A theoretical model incorporating social influence and cognitive processes to explain the adoption of the Internet of Things and smart connected objects (Article 2)

Abstract

It may take some time for innovations to prove their value and benefits to consumers. In this study, we extend the Technology Acceptance Model (TAM) with new antecedents adapted to the IoT and smart connected object (SCO) context. More specifically, in addition to TAM's main variables (i.e., perceived usefulness, perceived ease of use, intention to use, and real use), we investigate the roles of perceived well-being, perceived social image, privacy concerns, and innovativeness. We also study the differences in perceptions of SCO between non-users and innovators at year 1 (study 1), early adopters at year 2 (study 2), and the majority of users at year 3 (study 3). The data comes from 702 random respondents surveyed in a longitudinal study over 3 years. Structural equation modelling shows that the main TAM variables (e.g., perceived usefulness, perceived ease of use, intention to use, real use) are relevant in the SCO context. Utility benefits are the main reasons leading to acceptance, and a better well-being and social image lead to loyalty of use. Privacy concerns are the main obstacles to the adoption of SCO. This article aims at highlighting the factors of SCO acceptance according to the adoption stages from Kotler (1999).

Figure 14 sums up our main objectives and methodology for Article 2:

Article 2	OBJECTIVES	<ul style="list-style-type: none"> - Respond to calls for research (Anderson & Ortinou, 1988; Golder & Tellis, 1998; Huh & Kim, 2008; Shih & Venkatesh, 2004) - Extend the Technology Acceptance Model (TAM) with new antecedents adapted to the SCO context: perceived well-being, perceived social image, privacy concerns, and innovativeness - Study the differences of perceptions according to adoption stages (Kotler, 1999): non-users and innovators at year 1 (study 1), early adopters at year 2 (study 2), and the majority of users at year 3 (study 3)
METHODOLOGY	QUANTITATIVE STUDY (paper-and-pencil surveys)	
	207 non-users & early adopters	273 early majority of users
	Year 1	Year 2
		222 late majority of users
		Year 3
PUBLICATIONS	<p>Attié, E., & Meyer-Waarden, L. (2017). A theoretical model to explain the Internet of things adoption – extended model. EMAC 2017, Groningen, The Netherlands</p> <p>Attié, E., & Meyer-Waarden, L. (2017). The impact of consumer well-being and trust on the Internet of Things adoption and word-of-mouth intentions. AFM Conference 2017, Tours, France</p> <p>Attié, E., & Meyer-Waarden, L. (2016). A theoretical model incorporating social influence and cognitive processes to explain the adoption of the Internet of Things and smart connected objects, EMAC 2016, Oslo, Norway</p> <p>Attié, E., & Meyer-Waarden, L. (2016). Un modèle théorique incorporant l'influence sociale et des processus cognitifs pour expliquer l'adoption de l'Internet des objets. AFM Conférence 2016, Lyon, France</p> <p><u>Targeted journal</u>: Journal of Business Research</p>	

Figure 14: Main objectives and methodology (Article 2; adoption of SCO)

2.2.1. Introduction

In this research, we focus on smart connected objects (SCO) that can connect to smartphones through wireless networks (e.g., smart watches, smart clothes, smart home robots, etc.). We do not consider smartphones as these appeared in the 1990s and are thus no longer considered as innovations. SCO are defined as active, digital, networked, controlling things (Poslad, 2009), including artificial intelligence, that spontaneously adapt their features to external indicators, sometimes independently of pre-set parameters. Users' acceptance is a key determinant of these innovations' success (Dillon & Morris, 1996). It is therefore a high priority research issue to investigate relevant factors driving the adoption of SCO and to understand the perceived risks (Verhoef et al., 2017). Research has also shown that users may change their use and beliefs about technology over time (Ashraf et al., 2014; Rogers, 2003; Gilly et al., 2012).

This study builds on previous research concerning the relevance of the technology acceptance model (TAM; Davis, 1989) and its traditional variables (i.e., perceived usefulness, perceived ease of use, intention to use, real use). On the other hand, as the TAM is often considered insufficient to explain other and new antecedents of technology adoption (Benbasat & Barki, 2007; Chuttur, 2009), we enhance it by introducing other social and cognitive variables, such as perceived social image, well-being, innovativeness, and privacy concerns, which are under-investigated in the marketing and management literature (and above all in the SCO domain). Furthermore, the marketing literature on innovation diffusion has mostly focused on the pre-adoption process, and few studies examine post-adoption perceptions (Anderson & Ortinau, 1988; Golder & Tellis, 1998; Huh & Kim, 2008; Shih & Venkatesh, 2004). As research shows the importance of considering different adoption stages, this enhanced TAM is empirically tested over three years (2015-2018) with different stages of SCO adoption (e.g., non-users and innovators—stage 1—, the early majority—stage 2—, then the late majority of users—stage 3—) (Kotler, 1999). These stages happen before and after technology adoption. The adoption stages start with awareness (people start to hear about the technology thanks to massive advertising) and interest (people start looking for information about the technology), then evaluation (people try or have tried the technology), and then adoption (people decide to adopt and use the technology) (Kotler, 1999).

This article is organized in the following manner: after presenting the theory in section 2.2.2., the data and methodology are described in section 2.2.3.; then, section 2.2.4. shows the results, which is followed by section 2.2.5. where the results are discussed; section 2.2.6. defines the contributions of our article, and finally, the main conclusions, limits and future research directions are stated in section 2.2.7.

2.2.2. Literature review

2.2.2.1. Summary of the literature about technology adoption used in this research

Developing the TAM (Davis, 1989) seems to be common-sense in studying the adoption of SCO, as it is highly used and recommended by the literature, and described as one of the most influential theories of human behavior (King & He, 2006; Venkatesh et al., 2003). Meta-analyses on the TAM show a robust, significant, and powerful model with strong psychometric properties that can be used within different technology contexts (King & He, 2006; Lederer et al., 2000; Legris et al., 2003). However, the traditional main variables, perceived usefulness (PU), perceived ease of use (PEU), and intention to use (IU) (Hauser & Simmie, 1981) are criticized for a low predictive power and limitations regarding theories of consumer behavior in marketing (Bagozzi, 2007; Chuttur, 2009; Franz & Robey, 1986; Hu et al., 1999; Pikkarainen et al., 2004; Wu & Wang, 2005). The basic TAM is thus insufficient to explain technology adoption because it might neglect other important cognitive and social antecedents of new technology adoption and usage (Benbasat & Barki, 2007; Chuttur, 2009). Further research is recommended to deeper study the TAM and increase clarity regarding new variables and contexts (Wu & Lu, 2013). This research therefore builds on previous investigations to clarify the divergent opinions about the TAM by enhancing it with new social and cognitive variables. Furthermore, as existing literature in management and marketing science has not yet deeply focused on the adoption and use of SCO, our research brings out new marketing insights (Verhoef et al., 2017).

2.2.2.2. Conceptual framework and hypotheses

Our theoretical model and hypotheses are shown in Figure 15. It shows that SCO acceptance and adoption should be influenced by two main categories – technology benefits, with PU and PEU, and self-improvement benefits, with perceived well-being and perceived social image, while personality traits, such as innovativeness, and perceived risks, with privacy concerns, should moderate the conceptual model relationships.

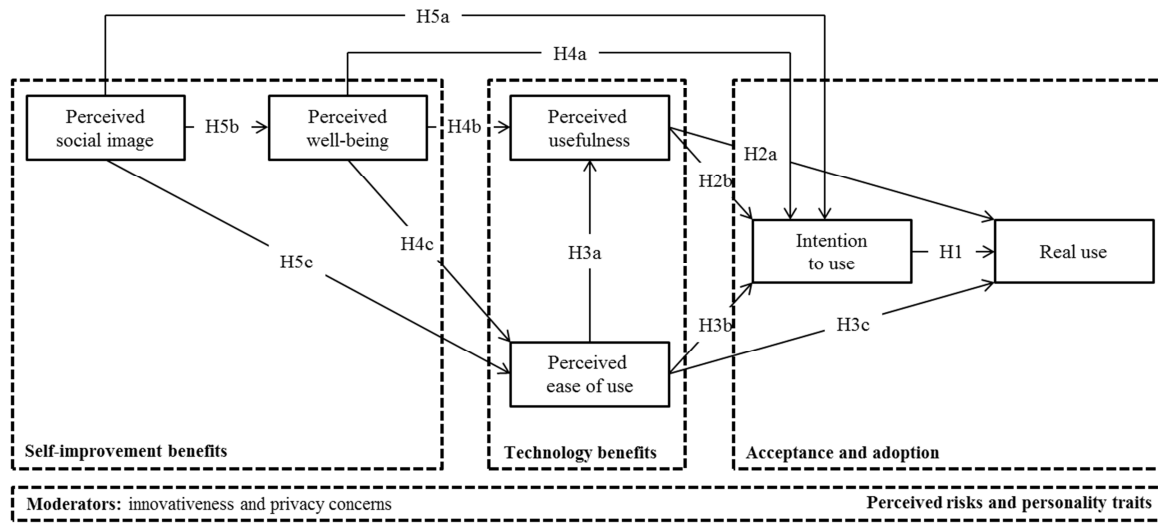


Figure 15: Conceptual model (*Article 2; adoption of SCO*)

The TAM brings an important contribution to the technology acceptance literature with intention to use (IU) as a direct determinant of use (Davis, 1989). Theoretical and empirical research supports a strong positive correlation between IU and real use (Dabholkar & Bagozzi, 2002; Davis, 1989; Lucas & Spitler, 1999; Mohd Suki & Mohd Suki, 2011; Vijayasarathy, 2004). Thus, we hypothesize:

H1: The IU of SCO has a positive influence on real use

Moreover, perceived usefulness (PU) and perceived ease of use (PEU) are the most used variables in the literature to explain technology adoption (Hauser & Simmie, 1981). PU is defined as the degree to which people believe that using a technology will help them to improve their performance (Davis, 1989). PEU is the degree to which the use of a technology is perceived as easy and free of effort (Davis, 1989). Indeed, PU and PEU are strong determinants of usage (Calantone et al., 2006; Davis, 1989; Taylor & Todd, 1995). Consumers have a more positive attitude toward a new technology when it is associated with

utility benefits such as PU or PEU (King & He, 2006; Venkatesh & Davis, 2000). PEU is also a direct determinant of PU and of technology adoption (e.g., IU and real use), since easy-to-use technologies seem more accessible and useful (Davis et al., 1989; Gefen & Straub, 2000; Pavlou, 2003; Taylor & Todd, 1995; Venkatesh, 1999; Venkatesh & Morris, 2000). Therefore, we hypothesize:

H2: The PU of SCO has a positive influence on (a) IU and (b) real use

H3: The PEU of SCO has a positive influence on (a) PU, (b) IU and (c) real use

However, consumer behavior theory provides evidence that functional and utility benefits are not sufficient to explain consumer attitudes (Chitturi et al., 2008; Christodoulides & Michaelidou, 2010). Research shows that the TAM neglects important factors in technology adoption (Benbasat & Barki, 2007; Chuttur, 2009) such as hedonic benefits (Chitturi et al., 2008; Sirgy, 2012). Hedonism reflects the emotional value of a given experience, perceived through feelings of enjoyment and playfulness (Grappi & Montanari, 2011). Hedonic motives appear to be relevant antecedents of technology adoption in consumer contexts (Bruner & Kumar, 2005; Childers et al., 2001; Dabholkar & Bagozzi, 2002; Hirschman & Holbrook, 1982; Kim & Forsythe, 2008; Kulviwat et al., 2007; Van der Heijden, 2004). It reflects the intrinsic motivations of technologies, such as the fun, enjoyment, and positive experiences consumers expect from using a technology (Brief & Aldag, 1977; Van der Heijden, 2004; Venkatesh et al., 2012). If hedonism is a short-term satisfaction, consumers' subjective well-being is seen as a long-term satisfaction (Zhong & Mitchell, 2012), which may be shaped by using SCO. Perceived well-being can be linked to physical health (Rozanski & Kubzansky, 2005), mental health (Su et al., 2014), consumer choices (Gilovich et al., 2015), and quality of life and hedonism (Ayadi et al., 2017; Costa & McCrae, 1980; Diener & Chan, 2011; Dolan et al., 2008; Hsee et al., 2009). It is the degree to which consumers perceive experiences in positive ways, through cognitive judgments and affective reactions, and without objective facts (Diener, 1984). Furthermore, the more users expect well-being while using a new technology, including an SCO, the more it enhances positive mental representations about technology use (Andreasen et al., 2012; Davis & Pechmann, 2013). Thus, consumers develop positive feelings toward the SCO and should intend to use this technology more often, positively influencing IU and PU. Users should therefore subsequently perceive SCO as easy to use (e.g., PEU) and useful (e.g., PU) in their daily life (e.g., Gu et al., 2010; Kim & Sundar, 2014). Therefore, we hypothesize:

H4: The perceived well-being from using SCO has a positive influence on (a) IU, (b) PU and (c) PEU

Moreover, the TAM does not consider the role of social influence, which could be relevant in innovation contexts (Bagozzi, 2007; Venkatesh & Davis, 2000). The Social Cognitive Theory shows that technology adoption is also impacted by social image (Bandura, 1986; Compeau & Higgins, 1995). Social image is defined as the degree to which the use of a product enhances a social status within a social group (Moore & Benbasat, 1991). Using an innovation, such as an SCO, can give a positive social image to users and improve acceptance as well as associated positive feelings (Kuisma et al., 2007; Rogers, 1983) like well-being. There is a link between the social value and hedonism, with the experience of use (Aurier et al., 2004). Therefore, consumers who perceive a new technology as conforming socially are more likely to use it since its use becomes a social action (Hellström, 2004). Performing a specific behavior consistent with group norms can achieve group membership, social support, and group identification through social image (Kiesler & Kiesler, 1969; Pfeffer, 1981). Consumers should thus develop positive group norms toward SCO and intend to use this technology more often. Furthermore, the more technologies' images are close to their users' self-image, the more users should find SCO easy to use, since the technology looks more familiar to them (Cowart et al., 2008; Sirgy, 1985). If people see themselves as innovative, their perceived self-image also influences the way they perceive technology, which should seem easier to them (Rogers, 1983). Thus, we hypothesize:

H5: The perceived social image through the use of SCO has a positive influence on (a) IU, (b) perceived well-being and (c) PEU

In addition, research has shown that the relationships influencing IU and real use are moderated by situational factors and normative constraints (Morwitz et al., 1993; Sheppard et al., 1988). The way SCO track and collect personal data can be perceived as too intrusive, which arouses privacy concerns (Awad & Krishnan, 2006; Hong & Thong, 2013; Phelps et al., 2001). Privacy concerns represent the degree to which users are concerned about the flow of their information (Phelps et al., 2000). When users perceive risks regarding the way their data is used by SCO, they tend to develop feelings of stress that subsequently lead to rejection of the technology (Lynch & Ariely, 2000). Therefore, we hypothesize:

H6: The effects hypothesized in H1, H2a, H2b, H3a, H3b, and H3c are weaker (stronger) when consumers have higher (lower) privacy concerns about SCO

Finally, according to the Innovation Diffusion Theory, people may react differently to new products due to personality traits, such as innovativeness (Rogers, 1983). Research has shown that technology optimism facilitates innovation adoption (Gilly et al., 2012). Innovative people have more positive beliefs about SCO than low innovative people (Agarwal & Karahanna, 2000; Eastlick & Lotz, 1999; Goswami & Chandra, 2013; Reynolds & Ruiz De Maya, 2013). Therefore, innovativeness is an interesting variable to study in relation to technology adoption (Agarwal & Prasad, 1998). More precisely, innovativeness is said to be a relevant moderator that impacts the links between the TAM variables (Agarwal & Prasad, 1998; Leonard-Barton & Deschamps, 1988; Mittal & Kamakura, 2001). As such, we hypothesize:

H7: The effects hypothesized in H1, H2a, H2b, H3a, H3b and H3c are stronger (weaker) for consumers with higher (lower) innovativeness

2.2.3. Methodology

2.2.3.1. Description of the scales

The variables are operationalized with validated scales from prior research (Table 10) that we adapted to the context of our study (e.g., ‘I use my SCO a lot in my daily life’). Items are measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). A five-point Likert scale is easier for respondents to visualize the measure without reducing the variance of the data (Podsakoff et al., 2003).

Construct	Adapted scale	Reasons to use this scale
Real use	Chau, 1996	- Scales with full sentences have a higher validity for use than with just number frequency (Amoroso & Hunsinger, 2009)
Intention to use	Davis, 1989	- Stable psychometric properties (Davis & Venkatesh, 1996)
Perceived usefulness		- A parsimony and predictive power (Mathieson, 1991) so the scales can apply to other contexts

Construct	Adapted scale	Reasons to use this scale
Perceived ease of use		- Research confirms the validity of these scales for technology acceptance (King & He, 2006)
Perceived well-being	Dimensions: - Happiness (Munzel et al., 2018) - Fun (Brief & Aldag, 1977) - Health (Howie et al., 1998) - Quality of life (Diener et al., 1985)	- A cognitive component of individual well-being, affective perception and overall well-being (Kiefer et al., 2013; Sheldon & Elliot, 1999) - Stable psychometric properties (Munzel et al., 2018) - Perceptions of well-being can be measured with happiness (Kiefer et al., 2013; Sheldon & Elliot, 1999), the fun perceived from using a technology (Brief & Aldag, 1977; Lowry et al., 2013; Van der Heijden, 2004; Venkatesh et al., 2012), health (Howie et al., 1998), and quality of life (Diener et al., 1985; Pavot & Diener, 1993, 2008)
Social image	Sweeney & Soutar, 2001	- Scale development through Churchill's (1979) approach, leading to stable psychometric properties (Sweeney & Soutar, 2001) - A reliable and valid scale in a post or pre-purchase situation (Sweeney & Soutar, 2001)
Privacy concerns	Hong & Thong, 2013	- Several studies use single-question scales, which has been criticized (Preibusch, 2013) - Significant differences between items and stable psychometric proprieties (Hong & Thong, 2013)
Innovativeness	Steenkamp & Gielens, 2003	- Systematic and integrated empirical data leading to a strong segmentation variable (Steenkamp & Gielens, 2003)

Table 10: Scales used (*Article 2; adoption of SCO*)

2.2.3.2. Administration of the survey and sample

The quantitative study is conducted from January 2015 to March 2018 in a classroom setting with paper-and-pencil surveys. The sample is composed of French students who are between 21 and 27 years old. Samples drawn from students facilitate comparability (Craig & Douglas, 2005) and this generation represents a promising market segment since they tend to be attracted to new technologies and to the Internet (Ashraf et al., 2014; Barbosa et al., 2018; Dimmick et al., 2007; McMillan & Morrison, 2006). The data include 107 non-users and 100 users using SCO for less than six months, 273 users using SCO for less than one year, and 222 users using SCO for less than two years. The sample sizes (N1 = 207; N2 = 273; N3 = 222) have a satisfying representativeness compared to the number of items used (Hinkin, 1995). There is no extreme value on one variable or multivariate data, which could influence the results. Table 11 presents the samples' gender characteristics.

Stage of adoption	Characteristic	N	Percentage	
Non-users and early adopters	Gender	Man	104	50.2%
		Woman	103	49.8%
Early majority of users	Gender	Man	162	59.3%
		Woman	111	40.7%
Late majority of users	Gender	Man	143	64.4%
		Woman	79	35.6%

Table 11: Descriptive characteristics of the samples (*Article 2; adoption of SCO*)

The percentages of men and women imply to test gender as a control variable of the conceptual model (Gefen & Straub, 1997; Venkatesh & Morris, 2000). Indeed, Table 11 shows that the proportions are roughly equivalent for the two first stages of adoption, but there are 64.4% of men at the last stage of adoption so it is important to know if gender has an influence on the results.

2.2.3.3. Reliability and validity of the items and scales

To validate the scales and keep or discard items, we use factor loadings and means by variable, which show how much a factor explains a variable (i.e., factor loadings > .70; Anderson & Gerbing, 1988), the Cronbach α for the reliability of the psychometric test (i.e., Cronbach α > .70; Nunnally, 1978), and the average variance extracted (AVE) for construct reliability (i.e., AVE scores > .50; Fornell & Larcker, 1981). The final items, scales, and reliability indicators are in Table 12. Scales show a good reliability and validity in the context of SCO and the variables meet the necessary conditions of normality for regressions.

Variables (scale reliability indicators)	<u>Factor loadings</u>			
	Stage	1	2	3
Use (Stage 1: Cronbach α = .98, AVE = .96, Mean = 1.96; Stage 2: Cronbach α = .84, AVE = .69, Mean = 3.86; Stage 3: Cronbach α = .85, AVE = .69, Mean = 3.97)				
I use a lot my SCO in my daily life		.97	.89	.89
I use my SCO in my daily life if possible		.97	.79	.79
I use frequently my SCO in my daily life		.97	.89	.89
I use my SCO in my daily life when needed		.94	.73	.73
	Mean	.96	.82	.82
Intention to use (Stage 1: Cronbach α = .84, AVE = .84, Mean = 1.53; Stage 2: Cronbach α = .81, AVE = .84, Mean = 2.07; Stage 3: Cronbach α = .81, AVE = .84, Mean = 3.45)				
Looking at its benefits, I intend to use my SCO in my daily life		.93	.92	.92
If I have access to my SCO, I intend to use it		.93	.92	.92
Since I have access to my SCO, I use it		.92	.93	.93
	Mean	.93	.92	.92
Perceived usefulness (Stage 1: Cronbach α = .86, AVE = .71, Mean = 3.33; Stage 2: Cronbach α = .87, AVE = .72, Mean = 3.78; Stage 3: Cronbach α = .86, AVE = .71, Mean = 3.89)				
My SCO is a good assistant during my daily life		.85	.86	.86
My SCO helps me to do my tasks faster and saving time		.83	.84	.83
My SCO makes my daily life easier		.88	.88	.88
My SCO is very useful		.81	.82	.80
	Mean	.84	.85	.84

Variables (scale reliability indicators)	<u>Factor loadings</u>		
	Stage	1	2
Perceived ease of use (Stage 1: Cronbach α = .85, AVE = .70, Mean = 3.86; Stage 2: Cronbach α = .77, AVE = .59, Mean = 4.12; Stage 3: Cronbach α = .77, AVE = .59, Mean = 4.21)			
I find it easy to use my SCO	.89	.83	.83
Using my SCO is clear and understandable	.88	.85	.86
I feel competent to use my SCO	.81	.67	.65
I feel that my SCO is adapted to my daily life	.75	.71	.71
Mean	.83	.77	.76
Perceived well-being (Stage 1: Cronbach α = .79, AVE = .62, Mean = 2.52; Stage 2: Cronbach α = .73, AVE = .57, Mean = 3.09; Stage 3: Cronbach α = .75, AVE = .58, Mean = 3.12)			
I like using my SCO as it is a fun distraction	.63	.51	.52
My SCO allows me to improve my health	.71	.76	.77
My SCO improves my quality of life	.88	.83	.83
In general, I feel well with my SCO	.90	.87	.88
Mean	.78	.74	.75
Perceived social image (Stage 1: Cronbach α = .96, AVE = .89, Mean = 2.16; Stage 2: Cronbach α = .90, AVE = .79, Mean = 2.41; Stage 3: Cronbach α = .90, AVE = .77, Mean = 2.39)			
My SCO gives me a more acceptable image	.93	.89	.88
My SCO improves how people perceive me	.97	.89	.87
My SCO gives others a good impression of me	.96	.89	.88
My SCO gives me a better social approval	.93	.87	.87
Mean	.95	.88	.87
Privacy concerns (Stage 1: Cronbach α = .89, AVE = .76, Mean = 4.11; Stage 2: Cronbach α = .90, AVE = .78, Mean = 3.55; Stage 3: Cronbach α = .90, AVE = .77, Mean = 3.42)			
I fear my SCO collects my information	.88	.88	.88
It bothers me when my SCO collects my information	.89	.91	.89
I fear my SCO uses my data for purposes I do not know about	.83	.89	.88
It bothers me to not control the information SCO get from me	.89	.85	.84
Mean	.87	.88	.87

Variables (scale reliability indicators)	<u>Factor loadings</u>			
	Stage	1	2	3
Innovativeness (Stage 1: Cronbach α = .74, AVE = .66, Mean = 3.08; Stage 2: Cronbach α = .75, AVE = .67, Mean = 3.26; Stage 3: Cronbach α = .76, AVE = .67, Mean = 3.38)				
If I hear about a new technology, I like to try it	.85	.82	.84	
I am usually the first one in my group to use a new technology	.85	.84	.83	
I feel able to use a new technology by myself	.73	.79	.80	
	Mean	.81	.82	.82

Table 12: Scales reliability indicators (*Article 2; adoption of SCO*)

2.2.3.4. Differences of means

The differences of means between the different adoption stages are stated in Table 13. We use Levene's test, which evaluates the equality of variance. It indicates that when p-values are below .05, the variances are significantly different.

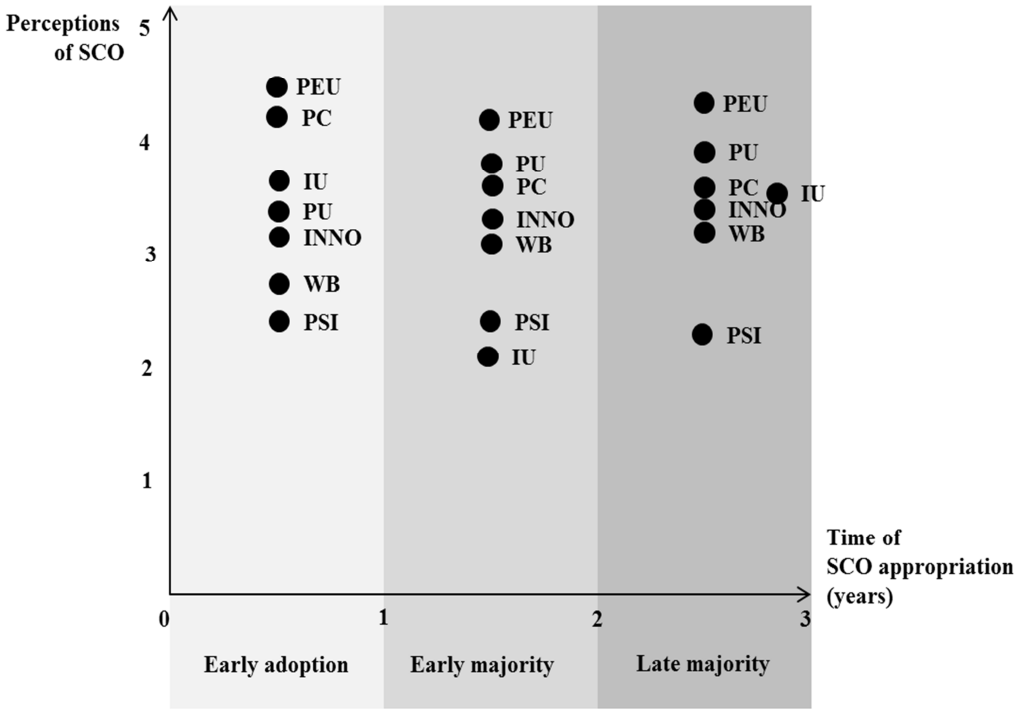
Construct	Mean			F (p-value)
	Stage 1	Stage 2	Stage 3	
Real use	1.96	3.86	3.97	37.71 (.00)
Intention to use	1.53	2.07	3.45	31.89 (.00)
Perceived usefulness	3.33	3.78	3.89	3.65 (.00)
Perceived ease of use	3.86	4.12	4.21	4.03 (.00)
Perceived well-being	2.52	3.09	3.12	2.93 (.00)
Perceived social image	2.16	2.41	2.39	2.33 (.00)
Privacy concerns	4.11	3.55	3.42	3.70 (.00)
Innovativeness	3.08	3.26	3.38	3.53 (.00)

Table 13: Differences of means (*Article 2; adoption of SCO*)

Table 13 shows that there are significant differences between the adoption stages in relation to real use, intention to use, PU, PEU, perceived well-being, perceived social image, privacy concerns, and innovativeness. With experience and time of use, real use increases with

experience of use (M1 = 1.96; M2 = 3.86; M3 = 3.97); IU increases (M1 = 1.53; M2 = 2.07; M3 = 3.45); PU increases (M1 = 3.33; M2 = 3.78; M3 = 3.89); PEU increases (M1 = 3.86; M2 = 4.12; M3 = 4.21); perceived well-being increases (M1 = 2.52; M2 = 3.09; M3 = 3.12); perceived social image has an inverted U-form and increases then decreases again (M1 = 2.16; M2 = 2.41; M3 = 2.39); privacy concerns decrease (M1 = 4.11; M2 = 3.55; M3 = 3.42); and innovativeness increases (M1 = 3.08; M2 = 3.26; M3 = 3.38).

Figure 16 shows the evolution of these perceptions according to the different stages of adoption.



SCO stands for smart connected objects; PEU for perceived ease of use; PC for privacy concerns; PU for perceived usefulness; INNO for innovativeness; WB for perceived well-being; PSI for perceived social image.

Figure 16: The perceptions of SCO according to the time of appropriation

Figure 16 shows that the main differences are with privacy concerns, which decrease over time, while perceived well-being, PU, PEU, IU, and innovativeness significantly increase over time; the variation of perceived social image increases with the early majority of users and decreases again with the late majority of users; the positive variation of innovativeness is less significant over time of use.

To assess discriminant validity, we check the square root of AVE for each variable. The bold numbers along the diagonal represent the square root of AVE, and the elements off diagonal are inter-scale correlations (Table 14).

Stage 1: Non-users and early adopters						
Constructs	Use	IU	PU	PEU	WB	PSI
Real use	.98					
IU	.43**	.90				
PU	.48**	.79**	.84			
PEU	.37**	.65**	.63**	.84		
WB	.27**	.64**	.61**	.48**	.78	
PSI	.36**	.57**	.54**	.36**	.50**	.95
Stage 2: Early majority of users						
Constructs	Use	IU	PU	PEU	WB	PSI
Real use	.82					
IU	.06**	.92				
PU	.55**	.38**	.85			
PEU	.42**	.29**	.52**	.77		
WB	.39**	.58**	.52**	.33**	.75	
PSI	.21**	.42**	.40**	.09**	.55**	.89
Stage 3: Late majority of users						
Constructs	Use	IU	PU	PEU	WB	PSI
Real use	.82					
IU	.34**	.92				
PU	.51**	.34**	.84			
PEU	.39**	.25**	.53**	.77		
WB	.39**	.57**	.49**	.32**	.76	
PSI	.19**	.40**	.35**	.06ns	.57**	.88

*** indicates p -value < .001; ** p -value < .01; * p -value < .1; IU stands for intention to use, PU for perceived usefulness, PEU for perceived ease of use, WB for perceived well-being, PSI for perceived social image.

Table 14: Correlations of the latent variables (*Article 2; adoption of SCO*)

Table 14 shows that the square root of AVE for each construct is higher than the correlations on the corresponding row and column and above .50, showing good discriminant validity (Fornell & Larcker, 1981).

2.2.4. Results

2.2.4.1. Structural model testing and its main effects

The data is analyzed via structural equation modelling (SEM) with Amos 21 from SPSS. We choose Amos because the multivariate normality analysis is acceptable (see Appendix 3A), each sample has at least 200 observations, and we intend to confirm theoretically assumed relationships. The estimated direct path coefficients are reported in Table 15

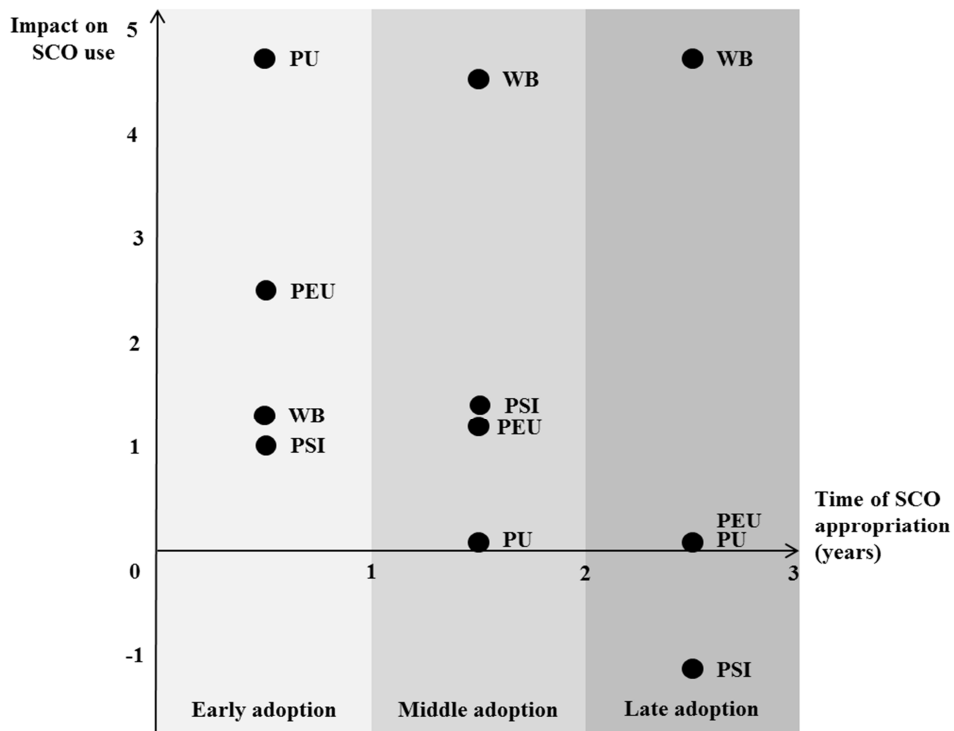
			Non-users and early adopters (1)		Early majority (2)		Late majority (3)	
Dependent variable	Independent variable	Hypothesis	β	t-value	β	t-value	β	t-value
Real use R ² (1) =.74 R ² (2) =.63 R ² (3) =.69	IU	H1	.07ns	.56	.14**	2.04	.17**	2.04
	PU	H2a	.09ns	4.17	.41***	6.25	.37***	4.92
	PEU	H3c	.43***	1.52	.16***	2.44	.15*	1.84
IU R ² (1) =.71 R ² (2) =.61 R ² (3) =.68	PU	H2b	.46***	8.01	.02ns	.35	.02ns	.35
	PEU	H3b	.21***	4.31	.11*	2.04	.08ns	1.31
	WB	H4a	.19***	3.76	.44***	6.93	.46***	6.24
	PSI	H5a	.14***	3.15	.15**	2.61	.12*	1.81
PU R ² (1) =.57 R ² (2) =.44 R ² (3) =.64	PEU	H3a	.45***	7.68	.39***	8.48	.41***	.44
	WB	H4b	.39***	5.04	.39***	4.55	.35***	.24
PEU R ² (1) =.25 R ² (2) =.35 R ² (3) =.35	WB	H4c	.40***	5.73	.33***	6.01	.42***	5.52
	PSI	H5c	.16***	2.22	-.14ns	-1.98	-.18**	-2.35
WB R ² (1) =.25 R ² (2) =.31 R ² (3) =.32	PSI	H5b	.51***	8.43	.55***	11.02	.57***	10.30

*** indicates p -value < .001; ** p -value < .01; * p -value < .1; IU stands for intention of use; PU for perceived usefulness; PEU for perceived ease of use; WB for perceived well-being; PSI for perceived social image

Table 15: Results of the estimated direct path coefficients (Article 2; adoption of SCO)

Table 15 shows that the predictive power of IU and real use are higher at stage 1 (respectively $R^2 = .74$; $R^2 = .71$) whereas the predictive power of PU, PEU, and perceived well-being are higher at stage 3 (respectively $R^2 = .64$; $R^2 = .35$; $R^2 = .32$). Moreover, IU has a positive influence on real use at stages 2 and 3, during the late adoption process (respectively $\beta = .14^{**}$; $\beta = .17^{**}$) but not at stage 1, during the early adoption ($\beta = .07ns$); H1 is supported for stages 2 and 3. Similarly, PU has a positive influence on real use at stages 2 and 3 (respectively $\beta = .41^{**}$; $\beta = .37^{**}$) but not at stage 1 ($\beta = .09ns$); H2a is supported for stages 2 and 3. PU has a positive influence on IU at stage 1 ($\beta = .46^{***}$) and is not significant at stages 2 and 3 (respectively $\beta = .02ns$; $\beta = .08ns$); H2b is only supported for time 1. Then, PEU has a positive influence on PU at stages 1, 2 and 3 (respectively $\beta = .45^{***}$; $\beta = .39^{***}$; $\beta = .41^{***}$); H3a is supported. However, PEU has a positive influence on IU at stages 1 and 2 (respectively $\beta = .21^{***}$; $\beta = .11^*$) and not at stage 3 ($\beta = .08ns$); H3a is supported for stages 1 and 2. PEU has a positive influence on real use at stages 1, 2 and 3 (respectively $\beta = .43^{**}$; $\beta = .16^{**}$; $\beta = .15^{**}$); H3c is supported. Perceived well-being has a positive influence on IU, PU and PEU over the whole adoption process, at stage 1 (respectively $\beta = .19^{**}$; $\beta = .39^{**}$; $\beta = .40^{***}$), stage 2 (respectively $\beta = .44^{**}$; $\beta = .39^{**}$; $\beta = .33^{***}$) and stage 3 (respectively $\beta = .46^{**}$; $\beta = .35^{**}$; $\beta = .42^{***}$); H4a, H4b and H4c are supported. Additionally, perceived social image has a positive influence on IU and on perceived well-being during the whole adoption process, at stage 1 (respectively $\beta = .14^{***}$; $\beta = .51^{**}$), stage 2 (respectively $\beta = .15^{**}$; $\beta = .55^{***}$), and stage 3 (respectively $\beta = .12^*$; $\beta = .57^{***}$); H5a and H5b are supported. Finally, perceived social image has a positive influence on PEU at stage 1 ($\beta = .16^{***}$), a non-significant influence at time 2 ($\beta = -.14ns$), and a negative influence at stage 3 ($\beta = -.18^{**}$); H5c is supported for time 1.

Figure 17 shows the variation of the impact of each variable on adoption over the stages of adoption.

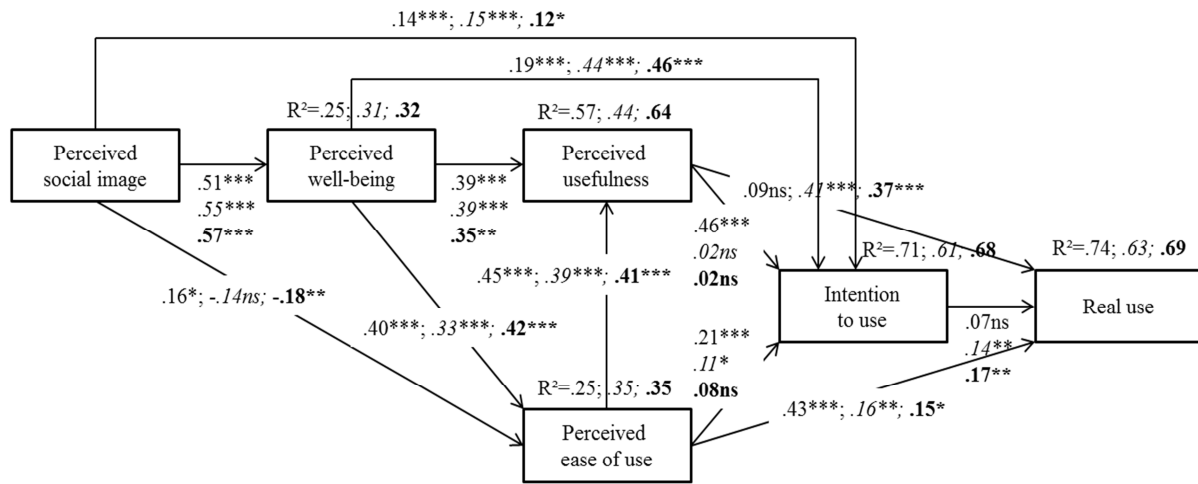


PU stands for perceived usefulness; PEU for perceived ease of use; WB for perceived well-being; PSI for perceived social image.

Figure 17: Impact of the antecedents of SCO adoption over time of appropriation

Figure 17 shows that the main decrease over time of adoption is with PU and PEU, while the impact of perceived well-being significantly increases over time; perceived social image increases at the middle adoption stage and considerably decreases for the late adoption.

Moreover, the results of the factorial invariance analysis show that the model fit indicators (Figure 18) are sufficient according to the guidelines ($\chi^2/DF < 5$ (Byrne, 2006), RMSEA $< .08$ (Browne & Cudeck, 1993), CFI $> .80$ (Bentler, 1990) and TLI $> .80$ (Bentler & Bonett, 1980)), thereby providing evidence that the model fit is acceptable for the whole adoption process, and it becomes better over time. Figure 18 summarizes the results.



*** indicates p-value < .001; ** p-value < .01; * p-value < .1; ns = non-significant
 Stage 1: $\chi^2/DF = 3.16^*$; RMSEA = .12; CFI = .99; TLI = .90
 Stage 2: $\chi^2/DF = 5.95^*$; RMSEA = .08; CFI = .97; TLI = .80
 Stage 3: $\chi^2/DF = 4.02^*$; RMSEA = .06; CFI = .98; TLI = .84

Figure 18: Conceptual model and model fit indicators (Article 2; adoption of SCO)

2.2.4.2. Moderating effects

To test the effects of the moderators, Process model 1 from Hayes is used (Table 16). Process is a regression path analysis modelling tool widely used in research for estimating moderation effects (Hayes et al., 2017). Details of the moderations are in Appendix 3B.

H6 Moderator: Privacy concerns						
Stage	H1 IU -> Use	H2a PU -> Use	H2b PU -> IU	H3a PEU -> PU	H3b PEU -> IU	H3c PEU -> Use
1	negative effect $\Delta R^2 = 1\%$	non-significant	non-significant	negative effect $\Delta R^2 = 1\%$	non-significant	negative effect $\Delta R^2 = 1\%$
2	non-significant	non-significant	non-significant	non-significant	negative effect $\Delta R^2 = 1\%$	non-significant
3	non-significant	negative effect $\Delta R^2 = 1\%$	non-significant	non-significant	negative effect $\Delta R^2 = 1\%$	negative effect $\Delta R^2 = 1\%$

H7 Moderator: Innovativeness						
Stage	H1 IU -> Use	H2a PU -> Use	H2b PU -> IU	H3a PEU -> PU	H3b PEU -> IU	H3c PEU -> Use
1	non-significant	positive effect $\Delta R^2=1\%$	non-significant	non-significant	positive effect $\Delta R^2=1\%$	positive effect $\Delta R^2=1\%$
2	non-significant	positive effect $\Delta R^2=1\%$	non-significant	positive effect $\Delta R^2=1\%$	positive effect $\Delta R^2=1\%$	positive effect $\Delta R^2=3\%$
3	positive effect $\Delta R^2=1\%$	positive effect $\Delta R^2=1\%$	positive effect $\Delta R^2=1\%$	non-significant	non-significant	positive effect $\Delta R^2=1\%$

IU stands for intention to use, PU for perceived usefulness, PEU for perceived ease of use

Table 16: Main moderating effects (*Article 2; adoption of SCO*)

Table 16 shows that privacy concerns negatively moderate the influence of IU on real use at stage 1 ($\Delta R^2 = 1\%$), the influence of PU on real use at stage 3 ($\Delta R^2 = 1\%$), the influence of PEU on PU at stage 1 ($\Delta R^2 = 1\%$), the influence of PEU on IU at stages 2 and 3 (for both $\Delta R^2 = 1\%$), and the influence of PEU on real use at stages 1 and 3 (for both $\Delta R^2 = 1\%$); H6 is partly supported.

Moreover, innovativeness positively moderates the influence of IU on real use at stage 3 ($\Delta R^2 = 1\%$), the influence of PU on real use at stages 1, 2 and 3 (for all $\Delta R^2 = 1\%$), the influence of PU on IU at stage 3 ($\Delta R^2 = 1\%$), the influence of PEU on PU at stage 2 ($\Delta R^2 = 1\%$), the influence of PEU on IU at stages 1 and 2 (for both $\Delta R^2 = 1\%$), and the influence of PEU on real use at stages 1, 2 and 3 (respectively $\Delta R^2 = 1\%$; $\Delta R^2 = 3\%$; $\Delta R^2 = 1\%$); H7 is partly supported. According to these results, studying privacy concerns and innovativeness as moderators of the relationships hypothesized helps to explain the model.

2.2.4.3. Control variables

In line with the literature, we include control variables to provide a stronger test of the hypotheses: gender (Gefen & Straub, 1997; Venkatesh & Morris, 2000), and experience of use (Davis, 1989; Venkatesh & Zhang, 2010). Table 17 shows the results of the control tests.

	R²	ΔR²	F (p-value)
Stage 1			
Without control variables	.74		
With gender	.74	0%	20.69 (.001)
With experience of use	.56	3%	19.96 (.001)
Stage 2			
Without control variables	.63		
With gender	.63	0%	25.33 (.001)
With experience of use	.64	0%	25.54 (.001)
Stage 3			
Without control variables	.69		
With gender	.70	0%	18.52 (.001)
With experience of use	.76	1%	49.96 (.001)

Table 17: Control variables indicators (*Article 2; adoption of SCO*)

Table 17 shows that gender is not a significant predictor of the model. However, at stage 1, there is a difference between users and non-users, increasing R² value. Studying the responses of SCO users and non-users increases the significance of the constructs rather than separating both set of data. Indeed, the TAM model brings out different results for SCO users and non-users. The literature showed that there could be different results regarding technology adoption when both groups are studied as a whole or separated, and that intentions to use are more predictable among users than non-users (Ramayah et al., 2002). In this study, when both users and non-users are used in the analysis, 74% of the variation in adoption can be explained by the model, and when the sample is split and analyzed separately, 73% of the variation in the adoption is explained with users and 56% is explained with non-users. This indicates that the model is more useful in predicting intention to use among early users and non-users studied as a whole set of data.

2.2.5. Discussion

One of our main goals is to test if the TAM and new variables are relevant within the French SCO market. Our model shows a satisfying fit according to literature standards that improves through the different adoption stages, suggesting that SCO experience positively changes consumer perceptions, following the disruptive innovation theory (Reinhardt & Gurtner, 2004). In addition, the proportions of variance demonstrated by the model vary from 69% to 74% according to the adoption stage. Research has shown that adding external variables to the TAM contributes to the explanation of the variance in technology use (Legris et al., 2003; Manis & Choi, 2018). Like Bagozzi (2007), we show that a sample of actual users increases the predictive power of the model and reduces the error variance of the data. It appears that actual users have already experienced the decision-making process implying a better knowledge and rationalization of their choices and behaviors in relation to SCO.

This study supports much previous research that says the TAM is a robust model that can be applied to new contexts of study (Adams et al., 1992; Bagozzi et al., 2000; Bruner & Kumar, 2005; Chau, 1996; Davis, 1989; Davis et al., 1989; Davis et al., 1992; Hu et al., 1999; Jang & Noh, 2011; Kim et al., 2009; Mathieson, 1991; Muk & Chung, 2005; Pikkarainen et al., 2004; Ramayah et al., 2002; Taylor & Todd, 1995; Venkatesh & Davis, 1996; Wu & Wang, 2005). Another theoretical goal is to study new antecedents, such as perceived well-being and perceived social image, which are also direct predictors of SCO adoption. Both are important in the late stages of adoption, namely stages 2 and 3, as they positively influence PU and PEU, and are thus reasons to continue using SCO. This confirms research and theories on new product diffusion which posit that new technology adoption is a temporal sequence of stages (Huh & Kim, 2008).

Concerning the tests of the hypothesis, IU influences real use when users have at least one year of experience with SCO, confirming theory (Porter & Donthu, 2006). In line with previous research, IU has a low predictive power on real use (Bagozzi, 2007; Chuttur, 2009; Franz & Robey, 1986; Hu et al., 1999; Pikkarainen et al., 2004; Wu & Wang, 2005). Our results also follow previous research showing that IU considerably decreases after one year of use, perhaps due to technology addiction effects, such as stress (Sheth, 1981; Szmigin & Foxall, 1998; Venkatesh, 2000; Venkatesh et al., 2003). Changes due to the adoption of a new technology could be stressful for consumers and thus have a negative impact on adoption

(Sheth, 1981; Szmigin & Foxall, 1998; Talke & Heidenreich, 2014). Other research has shown that early adopters tend to use the product or service more than those who have been using the product or service for a longer time (Huh & Kim 2008). Early adopters are better at developing schemas and need less cognitive efforts to understand and use new technologies (Huh & Kim, 2008).

Although utility benefits are the first factors of acceptance for early and middle adopters, PU has no influence on adoption for the late adopters (e.g., > 2 years of use). This result confirms previous research showing that early adopters are more attracted to basic technology functions than other users (Ashraf et al., 2014; Huh & Kim, 2008; Van Slyke et al., 2010). Indeed, consumers are more likely to adopt a technology if they perceive it as convenient and useful even though they do not enjoy using the technology (Saga & Zmud, 1994). However, studies about the influence of PU on IU are mitigated (Chen & Tan, 2004; Chen et al., 2007; Pavlou, 2003; Shan et al., 2005). Indeed, some studies show a stronger effect of enjoyment on attitude than PU (Bruner & Kumar, 2005; Childers et al., 2001). Furthermore, other research highlights the least role of PU in technology use (Adams et al., 1992; Bertrand & Bouchard, 2008; Hu et al., 1999), and the non-significant relationship between PU and IU (Bruner & Kumar, 2005; Johnson & Hignite, 2000). This difference could be explained by the difference between hedonic and utilitarian technologies (Childers et al., 2001). Therefore, our study supports the prior TAM research finding that PU is the primary determinant of technology adoption (Childers et al., 2001; Davis, 1989; Davis et al., 1989, 1992; Muk & Chung, 2005). It also suggests that PU is a powerful predictor of attitude toward technologies (Childers et al., 2001; Manis & Choi, 2018; Porter & Donthu, 2006; Rauschnabel et al., 2018).

While most research defines PU as a key determinant of technology acceptance, there are mixed results for PEU in the literature (Adams et al., 1992; Hu et al., 1999). In this study, PEU increases with experience of use and seems more important than PU, whereas existing research suggests the contrary (Van der Heijden & Verhagen, 2004). However, the influence of PEU on PU remains similar over experience of use, confirming previous research (Davis, 1989), whereas other researches did not find a significant link between PEU and PU (Childers et al., 2001; Dabholkar & Bagozzi, 2002). Furthermore, the influence of PEU on IU is more significant in the first adoption stage, confirming theory (Adams et al., 1992; Chen & Tan, 2004; Davis et al., 1989; Gentry & Calantone, 2002; Hong et al., 2002; Johnson & Hignite, 2000; Manis & Choi, 2018; Porter & Donthu, 2006; Rauschnabel et al., 2018; Saga & Zmud,

1994; Venkatesh & Davis, 2000; Zhang & Mao, 2008). After two years of use, PEU does not influence real use anymore (Muk & Chung, 2005). Schepers and Wetzels (2007) prove the significance of PEU and PU to IU and attitude, based on a meta-analysis of 51 articles.

SCO create positive experiences and well-being, subsequently leading to greater adoption of SCO (Andreasen et al., 2012; Davis & Pechmann, 2013). For the late adopters, only well-being benefits increase SCO re-usage. This is not in line with the TAM theory, which considers PU as the primary determinant of technology use and well-being as secondary (Childers et al., 2001; Davis, 1989; Davis et al., 1989, 1992). For other researchers, perceived well-being is the most powerful predictor of technology use (Bruner & Kumar, 2005; Childers et al., 2001; Dabholkar & Bagozzi, 2002; Manis & Choi, 2018; Muk & Chung, 2005; Pavlou, 2003; Rauschnabel et al., 2018). However, the literature suggests that perceived well-being could depend on the type of technology (Reinhardt & Gurtner, 2004). Concerning the influence of perceived well-being on PU and PEU, the direction of the link is not clear in the literature. Perceived well-being could improve PU and PEU by enhancing positive mental representations about the technology (Andreasen et al., 2012; Davis & Pechmann, 2013). On the other hand, PEU could also be an important predictor of use and well-being (Bruner & Kumar, 2005). In this study, we intend to examine the factors that influence the adoption of SCO and thus the TAM variables, so we investigate perceived well-being as a predictor of PEU, PU, and IU.

Additionally, although the influence of social benefits on attitude has been demonstrated in previous research (Muk & Chung, 2005), social benefits decrease with the time of adoption of SCO. The link with perceived well-being should be further investigated as studies have shown that even if users do not enjoy using a technology, they may still adopt this technology if it seems socially desirable (Saga & Zmud, 1994). In the case of SCO, results show that utility benefits are more important in the early stages of adoption, and perceived well-being is more important than social image in the later stages of adoption. It seems that for consumers, social image has a low effect on adoption and the more experience they have, the lower its influence. Culture also influences social influence, as the literature shows no effect on adoption with Koreans but a significant effect with Americans (Muk & Chung, 2005).

Regarding the barriers to the adoption of SCO, privacy concerns are the main risks perceived and obstacles to adoption (Buchanan & Ess, 2006). Indeed, risk perception is mainly based on the high potential for loss associated with the release of personal information to companies

(Dowling & Staelin, 1994). Therefore, privacy concerns involve uncertainty and user vulnerability (Barney & Hansen, 1994), and these influence the adoption of a new technology (Connolly & Bannister, 2007). In this research, privacy concerns decrease with the experience of use. In line with the privacy-personalization paradox, even when users perceive privacy concerns, they still intend to use SCO (Dimitriadis & Kyrezis, 2010; Sirdeshmukh et al., 2002). Users might believe that the benefits of personalization are higher than the costs of privacy loss (Hong & Thong, 2013; Xu et al., 2011). Moreover, the theory of the privacy calculus defines how users compare benefits and risks of personal data disclosure (Laufer & Wolfe, 1977). Thereby, when people perceive high personalization benefits and rewards (Awad & Krishnan, 2006; Lee & Cranage, 2011) or financial benefits (Culnan & Bies, 2003), they are more likely to provide personal information. The literature also showed that the moderating effect of privacy concerns becomes non-significant when users are aware of these risks, and feel control over the device, their personal data and the consequences of sharing (e.g., controlling data share, turning SCO off when not used) (Rauschnabel & Ro, 2016; Rauschnabel et al., 2018). Therefore, users show signs of resignation, and stop controlling their privacy (Rauschnabel et al., 2018). This is increased if users trust the technology (Dinev & Hart, 2006).

Research showed a significant link between innovativeness and technology adoption (Midgley & Dowling, 1978). Our results show that innovativeness is a significant moderator of the adoption process. This result is in line with the literature (Agarwal & Prasad, 1998; Leonard-Barton & Deschamps, 1988; Mittal & Kamakura, 2001; Reinhardt & Gurtner, 2004; Yi et al., 2006). Indeed, innovators perceive positive benefits from using SCO and have more positive attitudes toward using this type of technology (Agarwal & Karahanna, 2000; Eastlick & Lotz, 1999). However, as users recognize the value of a technology only after using it (Moore, 2014), the perceived benefits after use might be higher or lower according to their expectations (Jahanmir & Cavadas, 2018). Finally, the influence of innovativeness on SCO adoption varies according to the stages of adoption, as earlier adopters may not necessarily be more innovative than late adopters (Huh & Kim, 2008). It appears that less innovative people inform themselves more and thus, could be highly knowledgeable about technology risks (Goldsmith & Newell, 1997). Thus, in line with the literature, we confirm the importance of studying innovativeness as a moderator instead of a direct predictor of technology use (Yi et al., 2006).

2.2.6. Contributions

2.2.6.1. Theoretical contributions

This research brings new insights for the adoption of SCO in the marketing literature, since the overall majority of the research in this domain is done in engineering science and focuses on technical aspects. Our research thus contributes to the marketing and management science literature, which is lacking in explanations of factors related to the acceptance and use of SCO (Verhoef et al., 2017). More precisely, we build an extended TAM with confirmed relevant variables, namely perceived utilities (e.g., PU, PEU), and still few investigated factors, such as social and cognitive variables, perceived well-being, perceived social image, privacy concerns, and innovativeness. We then test the impact of these variables on intention to use and real use by taking into account different adoption and experience of use stages. We show that the relationships between the variables depend on different states of maturity of the market and user learning experiences (Davis et al., 1989; Keil et al., 1995; Kotler, 1999; Rogers, 2003).

The TAM's main variables (e.g., PU, PEU) are relevant in the SCO context, and the explanatory power of the model is improved by integrating experience of use. Therefore, this study enables us to define a significant theoretical model to explain SCO adoption. Moreover, we show that the extended TAM perfectly fits for SCO adoption even if the literature considers it useful only for utilitarian technologies and not for hedonic technologies (Benbasat & Barki, 2007). This result could also imply that SCO are considered as utilitarian technologies by consumers.

We show in our extended TAM the crucial role of little investigated antecedents like perceived well-being and perceived social image. Both variables are important once the SCO are adopted. Thus, we position our research in line with other researches that show that smart technologies should be linked to positive feelings in order to favor adoption and usage (e.g., Atzori et al., 2010; Etzioni, 1999; Harkin et al., 2016; Kluger & DeNisi, 1996; Porter & Heppelmann, 2014; Xia et al., 2012). Furthermore, PU becomes less significant with the experience of use (e.g., > 2 years of use), mostly being replaced by the importance of well-being. Consumers thus have different perceptions of SCO according to their position in the life cycle (Childers et al., 2001; Kotler, 1999): in the beginning, they see SCO as useful technologies, emphasizing the importance of PU; then, after use, they consider SCO as more

hedonic technologies. This explains why PEU becomes more important than PU with experience of use, as consumers are looking for more intuitive technologies.

Furthermore, this research confirms privacy concerns as the main barriers to SCO acceptance in the early stages of adoption (e.g., Buchanan & Ess, 2006; Hong & Thong, 2013). Thus, we position our research within the privacy-personalization paradox: with experience of use, even though users have privacy concerns, they still intend to use technologies due to technology benefits (Dimitriadis & Kyrezis, 2010; Sirdeshmukh et al., 2002). Lastly, regarding consumers' personalities, this research shows that innovativeness increases the adoption probability of SCO (Agarwal & Karahanna, 2000; Eastlick & Lotz, 1999).

2.2.6.2. Managerial contributions

Companies have to understand consumers' motivations to use SCO in order to adapt their products and services. Results show that early adopters first favor and perceive high usefulness and ease of use, confirming that utility benefits (e.g., PU, PEU) are the first reason to accept and adopt SCO (Davis, 1989; Davis et al., 1989; Calantone et al., 2006; Taylor & Todd, 1995). These utility benefits can be improved through social and well-being benefits (Bagozzi, 2007; Chitturi et al., 2008; Novak et al., 2000; Van der Heijden, 2004; Venkatesh & Davis, 2000). The development of products and services could thus focus on hedonic features to provide intrinsic usage motivation (Foreman et al., 2004). For example, self-image congruence with technology generates positive attitudes toward SCO and can improve adoption (Firat & Venkatesh, 1995). Companies could thus identify consumers' personalities and self-image to create congruent advertising and product design. This leads to developing useful, easy-to-use, and hedonic SCO (Firat & Venkatesh, 1995).

In addition, privacy concerns are the first and main obstacles to adoption, increasing consumer reluctance (Bhattacharjee, 2000). Solutions to remove this barrier to adoption are high-priority research issues (Verhoef et al., 2017). Therefore, companies should clearly communicate about secondary data usage and security policies, in order to increase trust (Shieh et al., 2013). This statement is timely relevant as most digital technologies lack security: indeed, 98% of mobile applications lack binary code protection and could be hacked, yet 50% of companies do not protect their applications (IBM, 2015). Thus, privacy issues should be a central managerial consideration in order to build consumer trust by giving more control to users. Finally, results show that consumer behavior toward SCO changes with the

different stages of adoption and experience of use. In line with this statement, our study shows the importance of targeting first innovators and early adopters with rational reasons and utility benefits (Von Hippel, 1986; Rogers, 2003); then, with advancing time, social and well-being benefits become more important. Indeed, innovators and early adopters are often seen as lead-users, who tend to adopt products ahead of others (Schweisfurth & Herstatt, 2015). Therefore, innovative consumers play a key role in the diffusion and adoption of new technologies, including SCO (Im et al., 2003). On the other hand, late adopters' adoption mainly depends on other users' opinions about the technology (Moore, 2014). Therefore, research and development strategies should focus on the likelihood of adoption by lead users rather than on the resistance of late adopters (Jahanmir & Cavadas, 2018).

2.2.7. Limits and further research directions

This research has limitations that give rise to ideas for future research projects about SCO.

First, the representativeness of the sample is a limitation. Our surveys are realized only with French students and the TAM variables might vary in other cultures (Straub et al., 1997) as behaviors may be shaped by values and lifestyles (Straub et al., 1997; Hofstede, 2001). Therefore, it would be interesting to replicate this study with representative samples in other countries to increase the generality of the findings (Bianchi & Andrew, 2012; Colton et al., 2010).

Another limit is that we consider all SCO (e.g., connected speakers, smart watches, connected lights, etc.) making it impossible to differentiate them. Further research should study the adoption of different and specific SCO; it could also be interesting to integrate different motivations of use (e.g., mandatory use, hedonic use, useful use, health motivation, work/productiveness motivation, etc.).

Moreover, we have no real-time behavior indicators and perceptions toward technology can differ with reality (e.g., Donaldson & Dunfee, 1994). Therefore, cooperation projects with SCO companies are recommended to get real-time behavioral data (e.g., Ahmadpour et al., 2016; Van Ittersum et al., 2013).

Finally, new laws, changing behaviors, and social influence might also modify the perceptions about SCO and thus the roles of the antecedents studied in this research.

Summary of contributions

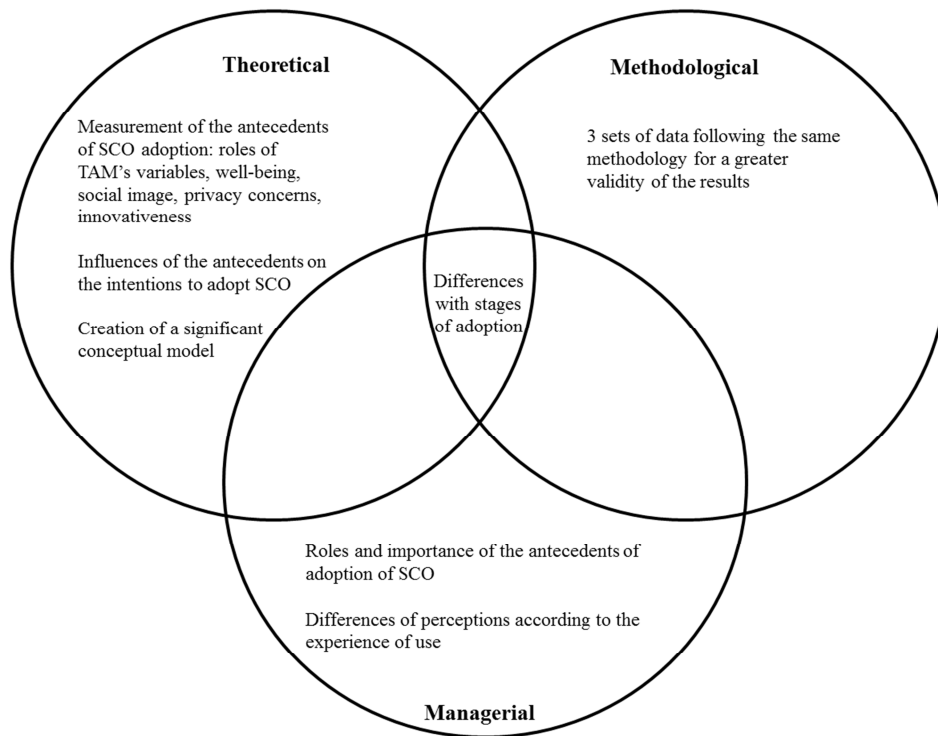


Figure 19: Summary of contributions (*Article 2; adoption of SCO*)

We summarize our contributions (Figure 19) in three categories:

- (1) Theoretical contributions: we measure antecedents of the IoT and smart technologies' adoption (TAM's main variables, perceived well-being, perceived social image, privacy concerns, and innovativeness), we test the influences of these antecedents on adoption, and we create a significant conceptual model to explain the adoption of the IoT and smart technologies;
- (2) Methodological contributions: we reproduce the same methodology with three sets of data according to the experience of use for a better understanding of adoption and use;
- (3) Managerial contributions: we show the importance of adoption antecedents, and the differences of perceptions according to users' experience of use.

Transition: from smart connected objects to the adoption of smart apps

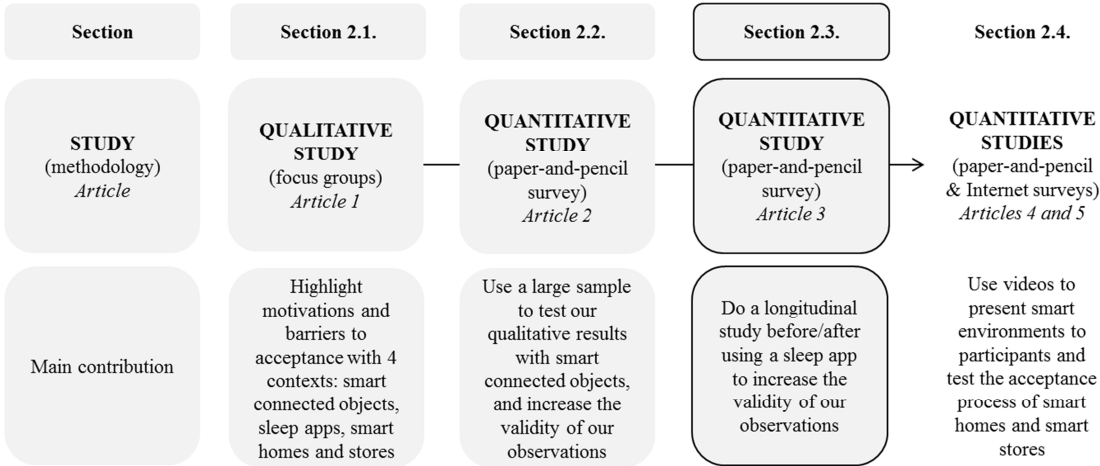
This quantitative research used three different sets of data (107 non-users and 100 users using SCO for less than 1 year, 273 users using SCO for less than 2 years, and 222 users using SCO for less than 3 years). This should develop the knowledge of our previous qualitative study about the acceptance of the IoT and smart technologies (*Article 1: “An exploratory qualitative analysis of the IoT technology acceptance: The roles of technology and self-improvement benefits, perceived risks, and user personalities”*). First, utility benefits convince consumers to become users. Nevertheless, the quantitative study (*Article 2: “A theoretical model incorporating social influence and cognitive processes to explain the adoption of the Internet of Things and smart connected objects”*) does not clearly evidence the fact that hedonic or social factors favour the adoption and re-use of SCO. Another limit already mentioned in Article 2 is the generalisation of our results regarding all categories of SCO since we could not differentiate them. Therefore, to tackle these limits, we perform a third study (*Article 3: “A longitudinal study to explain the adoption of sleep apps with the TAM, perceived well-being, quantified-self, privacy concerns and different types of personalities”*) and choose a smart technology easy to use, useful, with health and well-being motivations, and easily/free accessible for consumers. After trying ourselves three sleep apps during three months (e.g., one sleep app by month), we chose the easiest, less stressful with very few advertisings, cost free, available in the Google and Apple store, and recommended by medical staff (see <http://zz.isommeil.net/>). The reasons to choose a sleep app to deepen this thesis are the following:

1. A sleep app is a smart app because it wakes up users at the end of their sleep cycle, measuring sleep and health indicators while they are asleep. So, users do not control 100% of its functionalities. A sleep app is a smart app and is thus included in the IoT concept, allowing us to study another component of our topic.
2. A sleep app’s main goal is to improve sleep, good moods, habits, and thus well-being. A major goal is to test if smart technologies are seen as useful or hedonic (Benbasat & Barki, 2007) when it comes to health and well-being.
3. A sleep app can be used by everyone and has fewer constraints than a sport app which implies that participants are willing to do sports for our study. A step app (e.g., a mobile app measuring the number of steps done each day) could have been an alternative, but this is not a

‘smart’ app. Furthermore, even if it is a connected app, there are already studies about ‘basic’ or ‘connected’ apps, thus limiting potential contributions.

4. Sleep apps enable us to deepen the concept of well-being and privacy concerns as they collect the data while users cannot control it. Thereby, we can deepen the personalization privacy paradox (Hong & Thong, 2013) and the privacy calculus theory (Dinev & Hart, 2004).

Thereby, in section 2.3., we perform a quantitative longitudinal study to test the adoption of a sleep app before and after use, in order to increase the validity of the previous studies.



2.3. Smart apps acceptance and adoption: A longitudinal study to explain the adoption of sleep apps with the TAM, perceived well-being, quantified-self, privacy concerns and different types of personalities (Article 3)

Abstract

Mobile apps are increasingly becoming popular on the app market, requiring a better understanding of users' needs. As their adoption is expected to continue to rise in the near future (Scarpelli et al., 2017), current research is interested in examining their acceptance and real use. This research contributes to existing technology acceptance literature with a theoretical model that aims to explain the acceptance and adoption of a sleep app. The data is obtained from 182 respondents who tested a sleep app for one week. Structural equation modelling shows that perceived usefulness, perceived ease of use, intention to use, and real use are relevant in the adoption process of a sleep app, along with new and few investigated variables, such as perceived well-being, quantified-self, and privacy concerns. Another outcome of this study is that the adoption of sleep apps and perceptions differ according to different user personalities.

Figure 20 sums up our main objectives and methodology for Article 3:

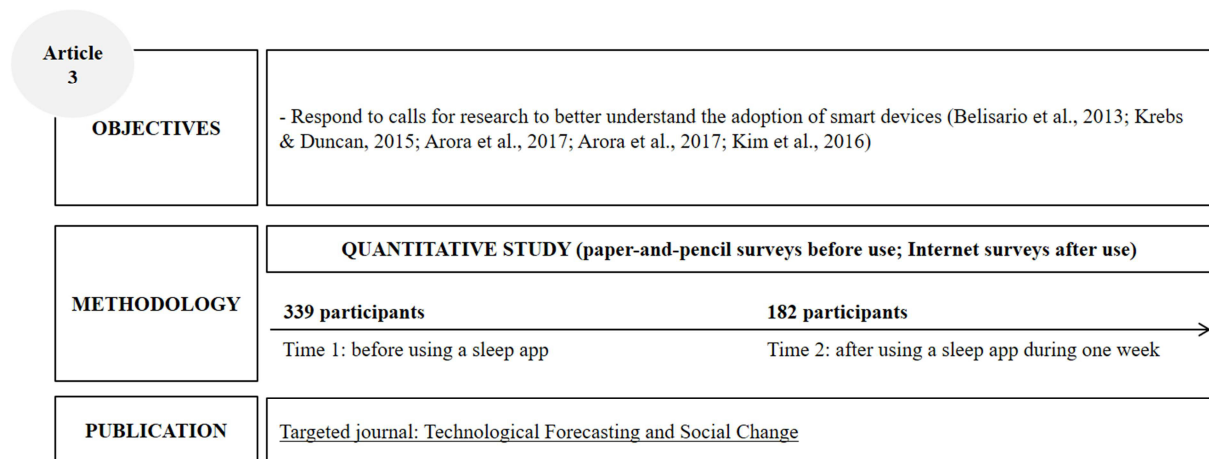


Figure 20: Main objectives and methodology (Article 3; adoption of sleep apps)

2.3.1. Introduction

For the last decades, mobile apps market showed a growing interest in health (Akter et al., 2011). Health apps aim to empower users by enabling them to self-manage health information and thus, their health conditions (Demiris, 2005; Kalem & Turhan, 2015). There are more than 40,000 health apps which focus on physical, mental and/or spiritual health (Krebs & Duncan, 2015). Mobile apps are one of users' most favoured ways of accessing the Internet (Lella & Lipsman, 2015), explaining this rapid growth and significance in business.

A mobile app is a software program that works with smartphones, or other connected objects, and that enables users to perform specific tasks (e.g., Harleen et al., 2014; Rakestraw et al., 2013) by collecting, storing, and providing real-time data. Based on the data collection, apps can provide a personalized advice and can automatically update the data and its functionalities (e.g., sleep apps wake up users at the end of their sleep cycle and not at the time set up). Through sensors built into smartphones, mobile apps can sense and analyze indicators from the environment and thus, are considered as 'smart'. Smart apps can be divided into six categories: games (e.g., smart virtual reality headsets), multimedia (e.g., music apps that automatically recommend playlists), productivity (e.g., smart schedules that notify users about traffic, schedules, localization), travel (e.g., smart GPS that automatically adapts to traffic and weather forecasting), education (e.g., smart boards, smart desks), and health (e.g., connected wristbands, sleep apps) (e.g., Harleen et al., 2014).

As health apps track real-time data (e.g., heart rate, sleep cycles, number of steps, diabetic control, prescription filling, etc.), they lead to important changes in health practices (Brennan, 1999). Health decisions and behaviours are mainly appreciated when smart devices offer an ease of use of self-tracking, self-knowledge and self-management (Ahern et al., 2006; Gibbons et al., 2011; Gustafson et al., 2002). On the one hand, health apps improve well-being and users' performances (Harkin et al., 2016) with a personalized feedback (Kluger & DeNisi, 1996). On the other hand, health devices negatively influence well-being and adoption over time (Etkin, 2016; Gonzalez et al., 2017). Similarly, users may have difficulties to see the link between apps' functionalities and their needs (Arora et al., 2017). Moreover, even though adoption is favoured by an expanded Internet connectivity, high mobile adoption, or health consciousness, smart apps can fail due to the difficulty of use, user reluctance, changing demand, strong competition, or security and radiation concerns (Attíe & Meyer-

Waarden, 2018). Thus, understanding the adoption of health apps are high priority issues in business and research (Arora et al., 2017; Krebs & Duncan, 2015) as there is still a lack of research in this topic (Arora et al., 2017; Kim et al., 2016).

When it comes to mobile apps, users are more likely to be influenced by various variables (Kim et al., 2016). Therefore, we add new antecedents of adoption that seem relevant in the context of health apps, such as quantified-self and personality traits (e.g., well-being and empowered personalities). To respond to these objectives, this quantitative survey is conducted with 182 participants who used a sleep app for one week, and who answered to surveys before (Time 1) and after use (Time 2). This allows us studying differences and reasons of acceptance or rejection, before then after using a sleep app.

This article is organized as follows: after presenting the theory in chapter 2.3.2., the data and methodology are described in chapter 2.3.3.; then, chapter 2.3.4. shows the results, which is followed by chapter 2.3.5., where the results are discussed; chapter 2.3.6. highlights our contributions; finally, we conclude with the limits and opportunities for further research in chapter 2.3.7.

2.3.2. Literature review

Aside from the TAM (Davis, 1986), the uses and gratification theory (Katz et al., 1974) is also an adequate predictive and explanatory theory to explains how people use the information from the media, through users' needs, goals, perceived benefits, and consequences of use (West & Turner, 2010). Many studies have extended the TAM with this theory (Zhang & Mao, 2008). This theory applies to sleep apps since they respond to users' (1) cognitive needs, to obtain specific information about sleep quality; (2) affective needs, to improve sleep quality and thus well-being and positive moods; (3) personal integrative needs, to develop an ability to use sleep apps and improve performances; (4) social integrative needs, to perform word-of-mouth actions and obtain an innovative social status; and (5) tension free needs, to feel relieved from eventual sleep tensions and entertain oneself (Katz et al., 1974). Figure 21 illustrates the theoretical model explaining the adoption of sleep apps.

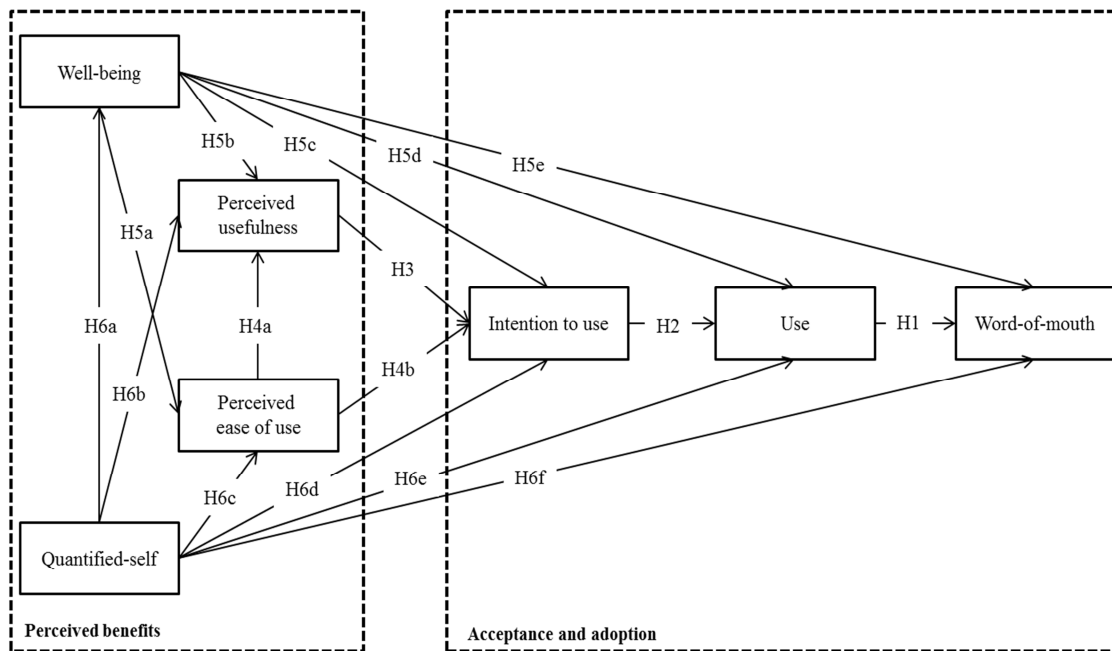


Figure 21: Conceptual model (Article 3; adoption of sleep apps)

2.3.2.1. Mediators

Word-of-mouth (WoM) is an interpersonal influence that plays an important role on product judgements and decision-making processes (e.g., Bansal & Voyer, 2000). Research also showed how adoption influences WoM intentions (Davis & Pechmann, 2013). Satisfaction of use has positive effects on the adoption and consequently on WoM intentions (e.g., Taghizadeh et al., 2013). Furthermore, the more people intend to use the app, the more they should use the app (Davis, 1989) and should be more willing to recommend it to others. Thereby, we hypothesize:

H1: Using the app has a positive influence on WoM (1) before and (2) after use

H2: The intention to use the app has a positive influence on use

According to the uses and gratification theory (Katz et al., 1974), people tend to seek for cognitive and useful needs (e.g., specific information, performance improvement, communication, etc.) when using the media (e.g., TV, the Internet, mobile apps, etc.). Mobile apps are useful when they manipulate sensitive data such as health information to respond to specific goals (Davis, 1989). Perceived usefulness (PU) is defined as the degree to which people believe a technology can help them to improve their performance (Davis, 1989); perceived ease of use (PEU) is the degree to which the use of a technology is perceived as

easy and free of efforts (Davis, 1989). Likewise, a higher PEU increases PU which both influence intention to use since users are reluctant to make efforts in using new technologies (Davis, 1989; Rauschnabel et al., 2015; Venkatesh, 1999). Furthermore, higher intentions to use a technology increase real use (Davis, 1989). Therefore, we hypothesize:

H3: PU has a positive influence on intention to use (1) before and (2) after use

H4a: PEU has a positive influence on PU (1) before and (2) after use

H4b: PEU has a positive influence on intention to use (1) before and (2) after use

Literature showed that well-being has a significant influence on consumer behaviour and technology use (Munzel et al., 2018). Perceived well-being is the degree to which consumers perceive experiences in positive ways, through cognitive judgments and affective reactions, without objective facts (Diener, 1984). Although a growing number of researches investigates the effect of smart technologies on well-being, the direction of the relationship needs clarification (Munzel et al., 2018; Steptoe et al., 2012). Perceived well-being includes senses of hedonism, such as feelings of happiness and enjoyment (Van der Heijden, 2004), overall health (e.g., sleep benefits) and quality of life (Attié & Meyer-Waarden, 2018). A greater well-being implies positive experiences, increasing usefulness and mental representations of ease of use (Andreasen et al., 2012; Davis & Pechmann, 2013). Moreover, the theory of flow (Csikszentmihályi, 1975) considers that well-being is a predictor of attitudes and behaviours, such as intention to use and real use (Mathwick et al., 2001). Furthermore, well-being has a strong positive influence on WoM intentions (Jones et al., 2006). The more users think the app can improve their well-being, the more they should be satisfied and willing to recommend it (e.g., Davis & Pechmann, 2013). Thus, we hypothesize:

H5a: Well-being has a positive influence on PEU (1) before and (2) after use

H5b: Well-being has a positive influence on PU (1) before and (2) after use

H5c: Well-being has a positive influence on IU (1) before and (2) after use

H5d: Well-being has a positive influence on use (1) before and (2) after use

H5e: Well-being has a positive influence on WoM (1) before and (2) after use

We consider self-improvement as the motivation to reach goals that will enhance some self-relevant aspects of the self, such as personal attributes or performance (i.e., the intellectual, moral, social or physical self; Sedikides & Strube, 1997). Quantified-self is the ability to collect data and manage health indicators to improve, among others, self-knowledge, health, and performances (Kozinets, 2012). The self-efficacy theory (Bandura, 1997) highlights the role of quantified-self in the adoption process and research has shown that self-control enhances well-being (Kiefer et al., 2013). This theory indicates that self-efficacy comes from personal control (linked to successes and failures), social learning (linked to the observation of other people), persuasion by others (linked to realistic compliments from others), and emotional and physical states (linked to health and feelings) (Bandura, 1997). Health apps are also self-tracking technologies, which guide users in a personalized way (Beck & Beck-Gernsheim, 2002; Lupton, 2016). Therefore, users become active participants interacting with technologies (Nafus & Sherman, 2014) which influence their decisions and behaviours (Mackenzie, 2013). People with a higher degree of quantified-self are more likely to use technologies that let them improve their self-assessment and self-management, as they perceive more usefulness and ease-of-use (Attie & Meyer-Waarden, 2018). These positive feelings while using the app should positively influence intention to use, real use and WoM intentions (e.g., Taghizadeh et al., 2013). Thus, we hypothesize:

H6a: Quantified-self has a positive influence on well-being (1) before and (2) after use

H6b: Quantified-self has a positive influence on PU (1) before and (2) after use

H6c: Quantified-self has a positive influence on PEU (1) before and (2) after use

H6d: Quantified-self has a positive influence on intention to use (1) before and (2) after use

H6e: Quantified-self has a positive influence on use (1) before and (2) after use

H6f: Quantified-self has a positive influence on WoM (1) before and (2) after use

2.3.2.2. Moderators

Privacy concerns arise when consumers worry about the collection of personal information and how the data is used (Etzioni, 1999; Hoffman et al., 1999; Shin, 2010). Privacy concerns, defined as the degree to which extent users are concerned about the flow of their information, remain the main reticence regarding smart technologies (Phelps et al., 2000). Companies might sell this information to third parties (e.g., other companies, advertisers) for marketing purposes (Hempel & Lehman, 2005) or proactively tailor their own service (e.g., Chellappa & Sin, 2005). Therefore, users can consider this as intrusive, arousing privacy concerns (Phelps et al., 2000). Research showed that the more people fear about privacy concerns, the less they intend to use technologies, decreasing intention to use and utility benefits (Dimitriadis & Kyrezis, 2010). Thereby, we hypothesize:

H7: The more users perceive privacy concerns, the lower will be the influence of the links hypothesized in H1, H2, H3, H4a, and H4b

Furthermore, perceived well-being can be linked to cognitive and emotional reactions due to experiences, and to personality traits (Diener et al., 1999; Kahneman et al., 1999). Some people with specific personality traits are more often able to feel well-being (Csíkszentmihályi, 1975). People with a high or low well-being personality are defined as more or less predisposed to recognize, accept, feel, and share senses of well-being, feeling positive feelings more deeply than the average people (e.g., Csíkszentmihályi, 1975; Mill, 1998; Olson, 1999; Zeanah & Fox, 2004). To them, well-being refers to a way of being, a state of the soul and a way of doing well (e.g., Guibet Lafaye, 2007). We can refer to the eudemonism theory linked to abilities to find a purpose with well-being (Ryan & Deci, 2001). Thus, people with a higher well-being personality are more interested by technologies improving feelings of hedonism, entertainment, or health (Attié & Meyer-Waarden, 2018). Users with a higher well-being personality should perceive a greater well-being while using the sleep app, leading us to the following hypothesis:

H8: The more users have a high well-being personality, the higher will be the influence of well-being on the other variables as hypothesized in H5a, H5b, H5c, H5d, and H5e

In the same vein, users with an empowered personality should feel more well-being (Kiefer et al., 2013) when using a smart technology. People with a high or low empowered personality

are defined as more or less predisposed to get, feel, then use senses of power with a willingness to do quantified-self through self-tracking, self-knowledge and self-management (e.g., Harris & Westin, 1991; Kozinets, 2012; Mill, 1998). A sleep app should attract them at first, but its ‘smart’ characteristics might frustrate them, as they cannot control all the functionalities of the sleep app. These people also have predispositions to convince other people through WoM actions, as they have an expert image (e.g., Nafus & Sherman, 2014). Thus, we hypothesize:

H9: The more users have an empowered personality the lower will be the influence of quantified-self on the other variables as hypothesized in H6a, H6b, H6c, H6d, H6e, and H6f

2.3.3. Methodology

2.3.3.1. Description of the methodology

This study is conducted in France, from October 2016 to March 2018, in a university classroom setting with paper-and-pencil surveys before use, and Internet surveys after use. Compared to paper-and-pencil surveys, Internet surveys eliminate confounding sources and the missing data (Parasuraman et al., 2006). It is advisable to use Internet surveys once respondents have prior experience with the technology to avoid issues of self-generated validity (Feldman & Lynch, 1988), explaining our choice to first conduct paper-and-pencil surveys.

Besides, samples drawn from students facilitate comparability (Craig & Douglas, 2005) and represent a promising market segment (Ashraf et al., 2014). Indeed, this generation plays an important role in the development and adoption of smart devices (Barbosa et al., 2018) and adopts smart technologies faster than other generations (Lepp et al., 2014). The fact that the sleep app is free should not influence use, if compared to paying apps (Kim et al., 2016).

First, the functionalities of the sleep app named iSommeil are presented, before students respond to a paper-and-pencil survey, and before using the app. After responding to the survey, they are asked to use the app for one week. Then, after use, they responded to a second Internet survey. Each respondent has an identification number to track each response between before and after use. Of the 339 students that responded to the survey before use, 182 responses are valid (72% women; Mean age = 20.4; SD = .82) (157 participants did not

answer after use or some questionnaires were not valid at one or both times). However, the sample size (N = 182) has a satisfying representativeness compared to the number of items used (Hinkin, 1995).

2.3.3.2. Reliability and validity of the items and scales

The constructs are measured with existing and adapted Likert scales from prior research, ranging from 1 (strongly disagree) to 5 (strongly agree). Table 18 shows the scales adapted and used in this article.

Construct	Adapted scale
Real use	Chau, 1996
Intention to use (IU)	Davis, 1989
Perceived usefulness (PU)	
Perceived ease of use (PEU)	
Perceived well-being	- Happiness: Munzel et al., 2018 - Fun/Hedonism: Venkatesh et al., 2012 - Health: Howie et al., 1998 - Quality of life: Diener et al., 1985
Social image	Sweeney & Soutar, 2001
Privacy concerns	Hong & Thong, 2013
Innovativeness	Steenkamp & Gielens, 2003
Word-of-mouth	Zeng et al., 2009
Quantified-self	Howie et al., 1998
Well-being personality	Csíkszentmihályi, 1975; Hock, 1962; Mill, 1998; Olson, 1999; Zeanah & Fox, 2004
Empowered personality	Kozinets, 2012; Harris & Westin, 1991; Hock, 1962; Mill, 1998

Table 18: Adapted scales used (*Article 3; adoption of sleep apps*)

To validate our scales and decide to keep or discard some items, construct validity is considered as acceptable with factor loadings above .70 (Anderson & Gerbing, 1988), scales are reliable with Cronbach α above .70 (Nunnally, 1978), and construct reliability is checked with an average variance extracted (AVE) above .50 (Fornell & Larcker, 1981). Table 19 shows the scales, final items and reliability indicators.

Scale (<i>scales reliability indicators</i>)	Factor loadings	
	Before (1)	After (2)
Use (<i>Time 1: Cronbach α = .94; AVE = .94; Time 2: Cronbach α = .87; AVE = .88</i>)		
I use a lot iSommeil	.97	.94
I use iSommeil in my daily life if possible	.97	.94
I use frequently iSommeil	.96	.92
I use iSommeil in my daily life when needed	.98	.96
Mean	.97	.94
IU (<i>Time 1: Cronbach α = .88; AVE = .81; Time 2: Cronbach α = .80; AVE = .73</i>)		
Regarding its advantages, I intend to use iSommeil	.90	.82
If I have access to iSommeil, I intend to use it	.92	.88
Since I have access to iSommeil, I use it	.88	.87
Mean	.90	.85
WoM (<i>Time 1: Cronbach α = .89; AVE = .90; Time 2: Cronbach α = .92; AVE = .93</i>)		
I would say positive things about iSommeil to other people	.95	.96
I would encourage friends and relatives to use iSommeil	.95	.96
I would recommend iSommeil to those who seek my advice about it	.93	.95
Mean	.94	.96
PU (<i>Time 1: Cronbach α = .90; AVE = .83; Time 2: Cronbach α = .92; AVE = .84</i>)		
iSommeil is good at assisting me in my daily life	.94	.92
iSommeil makes my life easier	.90	.91
iSommeil seems very useful to me	.90	.93
Mean	.91	.92
PEU (<i>Time 1: Cronbach α = .83; AVE = .75; Time 2: Cronbach α = .88; AVE = .83</i>)		
It seems easy to use iSommeil	.88	.92
Using iSommeil seems clear and understandable	.86	.90
It is easy for me to become competent at using iSommeil	.84	.91
Mean	.86	.91

Scale (<i>scales reliability indicators</i>)	Factor loadings	
	Before (1)	After (2)
Well-being (<i>Time 1: Cronbach $\alpha = .89$; AVE = .70; Time 2: Cronbach $\alpha = .91$; AVE = .73</i>)		
I feel good using iSommeil	.78	.88
iSommeil makes me feel happy	.77	.81
iSommeil improves my health and sleep conditions	.84	.82
iSommeil improves my quality of life	.87	.88
In general, I feel well with iSommeil	.90	.88
Mean	.83	.85
Quantified-self (<i>Time 1: Cronbach $\alpha = .87$; AVE = .71; Time 2: Cronbach $\alpha = .89$; AVE = .75</i>)		
Given iSommeil's information, I feel able to deal with my day	.84	.86
Given iSommeil's information, I understand my health/moods	.87	.83
Given iSommeil's information, I feel able to adopt a healthy lifestyle	.86	.89
iSommeil allows me to improve my sleep conditions	.80	.83
Mean	.84	.85
Privacy concerns (<i>Time 1: Cronbach $\alpha = .89$; AVE = .75; Time 2: Cronbach $\alpha = .89$; AVE = .77</i>)		
I am afraid iSommeil can collect my data	.89	.92
I am afraid about the type of data iSommeil collects about me	.87	.88
It bothers me that iSommeil collects my personal data	.88	.85
I fear iSommeil uses my data for other purposes	.81	.87
Mean	.86	.88
Well-being personality (<i>Times 1 and 2: Cronbach $\alpha = .70$; AVE = .62</i>)		
I often feel full of positive energy	.84	.84
I often generate lots of enthusiasm	.78	.78
I am sociable and open to others	.74	.74
Mean	.78	.78
Empowered personality (<i>Times 1 and 2: Cronbach $\alpha = .80$; AVE = .63</i>)		
I have a positive attitude toward myself	.72	.72
I am usually confident regarding my choices	.87	.87
I feel able to do things on my own	.79	.79
I am often able to deal with struggles in life	.77	.77
Mean	.78	.78

IU stands for intention to use, WoM for word-of-mouth, PU for perceived usefulness, PEU for perceived ease of use

Table 19: Scales reliability indicators (*Article 3; adoption of sleep apps*)

Moreover, to assess discriminant validity, the square root of AVE for each variable is checked (see Table 20). Bold numbers along diagonal represent the square root of AVE, and elements off diagonal are inter-scale correlations. The square root of AVE for each construct is higher than the correlations on corresponding row and column and above .50, showing good discriminant validity (Fornell & Larcker, 1981).

BEFORE USE							
Constructs	Use	IU	WoM	PU	PEU	Well-being	Quantified-self
Use	.97						
IU	.79**	.90					
WoM	.69**	.65**	.95				
PU	.63**	.68**	.67**	.91			
PEU	.12ns	.15ns	.30**	.19ns	.86		
Well-being	.56**	.56**	.59**	.66**	.14ns	.85	
Quantified-self	.65**	.64**	.63**	.74**	.04ns	.78**	.84
AFTER USE							
Constructs	Use	IU	WoM	PU	PEU	Well-being	Quantified-self
Use	.94						
IU	.77**	.85					
WoM	.80**	.65**	.96				
PU	.79**	.74**	.78**	.91			
PEU	.33**	.22**	.36**	.31**	.91		
Well-being	.68**	.62**	.72**	.74**	.29**	.85	
Quantified-self	.69**	.61**	.78**	.74**	.37**	.81**	.86

***=*p*-value < .001; **=*p*-value < .01; *=*p*-value < .1; IU stands for intention to use, WoM for word-of-mouth, PU for perceived usefulness, PEU for perceived ease of use

Table 20: Correlations of the latent variables (*Article 3; adoption of sleep apps*)

2.3.4. Results

2.3.4.1. Differences of means

Since we measure the acceptance of iSommeil before use, then its adoption after use, there might be some differences regarding the perceptions of antecedents (see Table 21). Levene's test, which evaluates the equality of variance, indicates that when p-values are lower than .05, the variances are significantly different.

Construct	Mean		F (p-value)
	Before use	After use	
Word-of-mouth	3.10	2.11	7.35 (.007)
Intention to use	2.89	2.17	1.51 (.22)
Perceived usefulness	2.67	1.67	6.78 (.01)
Perceived ease of use	4.03	3.58	12.56 (.001)
Perceived well-being	2.44	1.74	4.07 (.04)
Quantified-self	2.96	2.17	.011 (.91)

Table 21: Differences of means before and after use (*Article 3; adoption of sleep apps*)

Table 21 indicates that there are significant differences before and after use with WoM intentions, PU, PEU, and perceived well-being which all decrease after use; there is no difference of means before and after use with intention to use and quantified-self.

2.3.4.2. Control variables

In line with literature, control variables are included to provide a stronger test of the hypotheses: gender, which can have an influence on results (Gefen & Straub, 1997; Venkatesh & Morris, 2000), emotions (positive and negative), which can have a cognitive effect and a strong influence on decisions and behaviors (Kahneman et al., 1999) and it is advisable to include them as control conditions (Snyder & White, 1982; Parrott & Hertel, 1999), and innovativeness (e.g., willingness to adopt new things; Rogers, 1983) as our sample is used to mobile apps so there shouldn't be significant differences between people with

higher versus lower levels of innovativeness. Table 22 presents the statistical indicators of the control variables tests.

	R ²	ΔR ²	F (sig)
Before use			
Without control variables	.66		
With gender	.61	.05	2.16 (.10)
With moods and emotions	.58	.08	.11 (.91)
With innovativeness	.60	.06	-1.71 (.10)
After use			
Without control variables	.74		
With gender	.74	0	-.08 (.93)
With moods and emotions	.74	0	.86 (.38)
With innovativeness	.79	.05	-1.24 (.22)

Table 22: Control variables indicators (*Article 3; adoption of sleep apps*)

Table 22 shows that these control variables are not significant predictors of the model. Thereby, gender, moods and emotions, and innovativeness do not influence our theoretical model before and after use.

2.3.4.3. Structural model testing

The data is analyzed via structural equation modelling with Analysis of Moment Structures from Statistical Package for the Social Sciences (Amos 21 from SPSS). We choose Amos because the multivariate normality analysis is acceptable (Appendix 4A¹), the sample size is about 200 observations and we want to confirm theoretically assumed relationships (theory and conceptual framework section). The estimated direct path coefficients are reported in Table 23.

¹ A multivariate normality test checks if the data has a normal distribution. Although a considerable amount of the data in the PP-plots appears to fall on a straight line, the data is acceptable for analysis (Chambers et al., 1983). Skewness and Kurtosis indicators are in between -2 and 2 (Appendix 4A), showing a normal univariate distribution (George & Mallery, 2010).

			Before use (1)		After use (2)	
Dependent variable	Independent variable	Hypothesis	β coefficient	t-value	β coefficient	t-value
WoM R ² (1) = .66 R ² (2) = .74	Use	H1	/	/	.49***	8.30
	Well-being	H5e	.17*	1.87	.13*	1.87
	Quantified-self	H6f	.19*	7.70	.28***	7.70
Use R ² (1) = .62 R ² (2) = .73	Intention to use	H2	/	/	.56***	10.34
	Well-being	H5d	/	/	.10ns	1.47
	Quantified-self	H6e	/	/	.26***	3.61
Intention to use R ² (1) = .58 R ² (2) = .57	PU	H3	.68***	8.87	.74***	14.88
	PEU	H4b	.15*	1.49	.21**	2.09
	Well-being	H5c	.02ns	.19	.07ns	.85
	Quantified-self	H6d	.31*	2.21	.20*	2.05
PU R ² (1) = .51 R ² (2) = .55	PEU	H4a	.14*	2.06	.09*	1.99
	Well-being	H5b	.22*	2.00	.31***	4.04
	Quantified-self	H6b	.56***	5.04	.52***	6.79
PEU R ² (1) = .18 R ² (2) = .11	Well-being	H5a	.28*	1.69	.29***	4.07
	Quantified-self	H6c	-.18ns	-1.08	.30***	4.26
Well-being R ² (1) = .13 R ² (2) = .10	Quantified-self	H6a	.78***	11.96	.83***	19.99

*** indicates p -value $< .001$; ** p -value $< .01$; * p -value $< .1$; ns = non-significant; WoM stand for word-of-mouth, PU for perceived usefulness, PEU for perceived ease of use.

Table 23: Results of the estimated direct path coefficients (*Article 3; adoption of sleep apps*)

Table 23 indicates that the predictive power of WoM, use, and PU are lower before use (respectively $R^2 = .66$; $R^2 = .62$; $R^2 = .51$) than after use ($R^2 = .74$; $R^2 = .73$; $R^2 = .55$). Besides, the predictive power of IU, PEU, and perceived well-being are higher before use (respectively $R^2 = .58$; $R^2 = .18$; $R^2 = .13$) than after use (respectively $R^2 = .57$; $R^2 = .11$; $R^2 = .10$). Moreover, use has a positive influence on WoM before and after use (respectively $\beta = .46***$; $\beta = .49***$); H1 is supported. Besides, IU has a positive influence on use before and after use (respectively $\beta = .63***$; $\beta = .56***$); H2 is supported. Then, PU and PEU both have a positive influence on IU before use (respectively $\beta = .68***$; $\beta = .15*$) and after use

(respectively $\beta = .74^{***}$; $\beta = .21^{**}$); H3 is supported. Moreover, PEU has a positive influence on PU before and after use (respectively $\beta = .14^{***}$; $\beta = .09^*$); H4a is supported. PEU also has a positive influence on IU before and after use (respectively $\beta = .15^*$; $\beta = .21^{**}$); H4b is supported. Furthermore, well-being has a positive influence on PEU before and after use (respectively $\beta = .28^*$; $\beta = .29^{***}$); H5a is supported. In addition, well-being has a positive influence on PU before and after use (respectively $\beta = .22^*$; $\beta = .31^{***}$); H5b is supported. However, well-being does not have a significant influence on IU before and after use (respectively $\beta = .02_{ns}$; $\beta = .07_{ns}$); H5c is not supported. Similarly, well-being does not have a significant influence on use before and after use (respectively $\beta = .05_{ns}$; $\beta = .10_{ns}$); H5d is not supported. Yet, well-being has a positive influence on WoM before and after use (respectively $\beta = .17^*$; $\beta = .13^*$); H5e is supported. Then, quantified-self has a positive influence on well-being before and after use (respectively $\beta = .78^{***}$; $\beta = .83^{***}$); H6a is supported. Moreover, quantified-self has a positive influence on PU before and after use (respectively $\beta = .56^{***}$; $\beta = .52^{***}$); H6b is supported. Quantified-self does not influence on PEU before use ($\beta = -.18_{ns}$) but it positively influences PEU after use ($\beta = .30^{***}$); H6c is supported at Time 2. In addition, quantified-self has a positive influence on use before and after use (respectively $\beta = .31^*$; $\beta = .20^{***}$); H6d is supported. Furthermore, quantified-self has a positive influence on use before and after use (respectively $\beta = .19^*$; $\beta = .26^{***}$); H6e is supported. Finally, quantified-self has a positive influence on WoM before and after use (respectively $\beta = .19^*$; $\beta = .28^{***}$); H6f is supported.

Besides, the factorial invariance analysis shows acceptable model fit indicators ($\text{Chi}^2/\text{DF} < 5$ (Byrne, 2006), $\text{RMSEA} < .08$ (Browne & Cudeck, 1993), $\text{CFI} > .80$ (Bentler, 1990), $\text{TLI} > .80$ (Bentler & Bonett, 1980)) (see Table 24).

	Chi²/DF	RMSEA	CFI	TLI
Before use	3.29*	.11	.97	.87
After use	2.12 _{ns}	.05	.99	.99

* indicates $p\text{-value} < .1$

Table 24: Model fit indicators (*Article 3; adoption of sleep apps*)

2.3.4.4. Moderating effects

To test the moderating effects, Process Model 1 (Hayes, 2012) is used. Process is a regression path analysis modelling tool widely used in research for estimating moderation effects (Hayes et al., 2017). Appendix 4B presents the details of the moderating effects.

Results show that privacy concerns negatively moderate the influence of use on WoM before use ($\Delta R^2 = 1\%$), and the influence of IU on use before and after use (respectively $\Delta R^2 = 1\%$; $\Delta R^2 = 1\%$); H7 is partly supported. Besides, a well-being personality positively moderates the influence of perceived well-being on PU before and after use (respectively $\Delta R^2 = 1\%$; $\Delta R^2 = 1\%$), the influence of perceived well-being on IU before and after use (respectively $\Delta R^2 = 2\%$; $\Delta R^2 = 2\%$), the influence of perceived well-being on use before and after use (respectively $\Delta R^2 = 1\%$; $\Delta R^2 = 1\%$), and the influence of perceived well-being on WoM before and after use (respectively $\Delta R^2 = 1\%$; $\Delta R^2 = 1\%$); H8 is supported. Furthermore, an empowered personality negatively moderates the influence of quantified-self on perceived well-being before and after use (respectively $\Delta R^2 = 1\%$; $\Delta R^2 = 1\%$), the influence of quantified-self on IU before and after use (respectively $\Delta R^2 = 1\%$; $\Delta R^2 = 1\%$), the influence of quantified-self on use before and after use (respectively $\Delta R^2 = 1\%$; $\Delta R^2 = 1\%$), the influence of quantified-self on WoM before use ($\Delta R^2 = 1\%$); H9 is partly supported.

2.3.5. *Discussion*

Results show that the predictive power of use and WoM is higher after use, suggesting that people rather speak about an app they have already tried, if it gives them a positive experience through well-being, and/or rational benefits like usefulness and quantified-self. This confirms theories saying that consumers share what gives them positive emotions (Berger & Milkman, 2012), and what seems useful (Berger, 2014). Moreover, when consumers are not satisfied with a service, they are more likely to do negative WoM (Audrain-Pontevia & Balagué, 2008; Kim et al., 2016). Moreover, the adoption of a sleep app is first influenced by utility reasons (e.g., usefulness, quantified-self), then by positive feelings (e.g., well-being). This is in line with research showing that a rational message generates higher intentions to use a health service, and positive feelings lead to a higher use of services (Zhang et al., 2014). In this study, PU has a significant influence on intention to use, along with PEU that positively influences PU, suggesting that the main TAM variables remain relevant in the context of sleep

apps, in line with past researches (Chen & Tan, 2004; Pavlou, 2003). Besides, PEU is only influenced by well-being, confirming that positive feelings enhance mental representations about the ease of use of a technology (Andreasen et al., 2012; Davis & Pechmann, 2013). However, PEU is not influenced by quantified-self before use, and only after use, suggesting that people need to test the app so that the link becomes relevant. This link between ease of use and senses of personal power has also been demonstrated in previous research (Birmingham-McDonogh & Eiben, 2015).

However, privacy concerns play an important role in the adoption of a sleep app. Removing barriers to adoption is a high-priority research issue to improve adoption (Verhoef et al., 2017). Privacy concerns lower the influences of the variables on WoM intentions and adoption, after using the sleep app. However, results show that utility benefits can compensate those privacy concerns. If people perceive the app as useful, it gives them a rational reason to use it, decreasing privacy concerns, in line with the privacy paradox (Dimitriadis & Kyrezis, 2010; Sirdeshmukh et al., 2002). Research also showed that the benefits of personalization can lower the perceptions of privacy loss (Hong & Thong, 2013; Xu et al., 2011). Consumers perceive companies as more benevolent if private information and engagements are respected, and with high personalization benefits (N'Goala & Cases, 2012).

Furthermore, people with a higher well-being personality feel more positive feelings while using the sleep app. The match between personality and the perception of a digital entity has a significant effect on whether or not the user is willing to be emotionally attached to this technology (Wang et al., 2016). Attachment is defined as a strong connection between a person and a specific person, object, firm or brand (Malär et al., 2011). Therefore, people with a higher well-being personality have more positive feelings and could develop a higher attachment to sleep apps. This follows the eudemonism theory linked to people's abilities to find a purpose with well-being (Ryan & Deci, 2001). Besides, people with a high-empowered personality seem to appreciate less the app, perceiving lower feelings of well-being and lower intentions of use. For high-empowered people, using the sleep app decreases WoM intentions and utility benefits after use. This is not in line with theory, as senses of control should improve perceptions toward a technology (Kiefer et al., 2013). However, with a sleep app, users could improve self-knowledge regarding sleep quantity and quality, but could not control all its parameters (e.g., Cases, 2017).

2.3.6. Contributions

The main contribution of this research is to highlight relevant antecedents (TAM's main variables, perceived well-being, quantified-self, privacy concerns, and personality traits) of the adoption of a sleep app. Theoretical, methodological and managerial contributions are presented below.

2.3.6.1. Theoretical contributions

This research contributes to the literature by defining a theoretical model which explains the adoption of a sleep app, with, to our best knowledge, new or few investigated variables such as well-being and quantified-self (Benbasat & Barki, 2007; Davis, 1989; Venkatesh et al., 2012). This model shows that TAM's main variables (PU, PEU, IU and real use) are relevant (e.g., Chen & Tan, 2004; Pavlou, 2003) in the context of sleep apps. Our results confirm that even if a sleep app is considered as a hedonic technology since it should improve sleep and health indicators, it can also be perceived as a useful technology with its quantified-self properties (e.g., manage sleep quantity and quality) (Benbasat & Barki, 2007).

Moreover, this research shows that first, acceptance is mostly influenced by utility expectations (e.g., PU, quantified-self), then actual use is favoured with positive feelings (e.g., well-being). We thus position our research in one stream of the literature which states that well-being is important to continue using smart technologies (Zhang et al., 2014). Besides, perceived well-being influences PEU by enhancing mental representations about the use of the sleep app (e.g., Andreasen et al., 2012; Davis & Pechmann, 2013). However, quantified-self influences PEU only after use, showing that trying the app improves the link between quantified-self benefits and the ease of use of the sleep app (e.g., Bermingham-McDonogh & Eiben, 2015).

Lastly, we show that personalities moderate adoption and usage. Users with a higher well-being personality value more the app after use than before, whereas people with a higher empowered personality value more the app before use than after. This could be explained by the 'smart' characteristics of the app, allowing high well-being users to let go any pressure and allow technologies to control their sleep if they believe it is for their own good, while high empowered people miss the control they usually like. This finding shows the importance

of doing segmentation with types of users, when studying technology adoption (Scherer, 1986).

2.3.6.2. Methodological contributions

The methodological contribution is that we study the adoption of a smart/sleep app with a longitudinal study, following the responses before use and after use.

2.3.6.3. Managerial contributions

Our main managerial implication is that utility benefits mainly increase acceptance, followed by well-being benefits that increase re-use. Therefore, sleep apps should be driven by real needs (e.g., improve sleep conditions, manage sleep time, etc.), giving the right information (e.g., number and time of deep and restless sleep cycles) at the right time for users. Further, sleep apps should mainly communicate about useful and easy functionalities to convince potential adopters (e.g., Chang et al., 2005; Szajna, 1996). Thus, simplifying self-tracking, self-knowledge and self-management could enable people to easily track their sleep quality, collect personal data, and manage their sleep. PU is also increased through relational, hedonic and emotional benefits (Novak et al., 2000). A greater well-being with easy to use apps should bring more positive experiences, and subsequently lead to a greater adoption, use, and re-use (Andreasen et al., 2012; Davis & Pechmann, 2013).

Furthermore, real experience lowers the perceptions of usefulness, well-being, and adoption. One explanation for this might be related to the following reasons given by some participants: the app did not always work properly or there was user resistance after try (users did not appreciate to be waken up 30 min before the set up time, the register of movements or breathing indicators during the night did not work, and the app had access to information that seemed too intimate). Thereby, experience decreases both PU and PEU which are linked (i.e., the more the app seems difficult to use, the less useful it seems to be), and subsequently decreases well-being. Moreover, quantified-self has not changed, probably due to the fact that users do not control the app since the app controls their sleep quantity.

Another managerial implication is that privacy concerns remain the primary obstacle to adoption, significantly impacting consumer reluctance. The data security must be a central topic in product development, data policies, and communication, since trust attracts and

retains users (Bhattacharjee, 2000; Hengstler et al., 2016; Shieh et al., 2013). 98% of mobile apps lack binary code protection and could be hacked, and 50% of companies do not protect their apps (IBM, 2015), showing the importance of these timely concerns. However, existing research showed that, even if users are concerned about privacy issues, they should keep using the technology if they believe the benefits of personalization are higher than the privacy loss (Xu et al., 2011). Respondents rated lower privacy concerns before use than after use, which is likely because the information disclosure becomes real and tangible after use (e.g., recording of sounds and movements during the night, access to the camera, microphone, other phone data). Trust toward a brand positively influences WoM and affective commitment (N'Goala, 2010). Thereby, sleep apps should be transparent about the way the data is collected, stored, used, and eventually resold.

Nevertheless, the phenomenon of empowerment appears when users perceive an ability to control personal outcomes (Kiefer et al., 2013). Studies have shown that providing resources and power to users could positively influence their preferences and behaviours toward a technology (e.g., Fuchs et al., 2010). Yet, people with a higher well-being personality seem to know how to manage the app better. They feel more well-being, intend to use the app more often and recommend it more than others. Furthermore, as users can influence more peers with the use of the Internet (Pires et al., 2006), providing a social network button to share information from the app should make it easier for users to perform WoM actions.

2.3.7. Limits and further research directions

This study has some limits, leading to future research directions. Firstly, research has shown that intention to use and adoption could change over time (Ashraf et al., 2014; Davis et al., 1989; Keil et al., 1995). More specifically, health devices can decrease feelings of well-being, mainly due to feelings of stress, too much control and addiction consequences over the years (e.g., Etkin, 2016). However, this study tests the differences of perceptions about a sleep app before use and after only one week of use. Therefore, doing the same experimentation for a longer period (i.e., months or years) is recommended as it could reveal eventual changes on the main mediating and moderating effects.

Moreover, future research could compare results with different sleep apps to understand which features are the most attractive or if there is a difference between a paid and a free sleep app for example (Kim et al., 2016).

Besides, according to the theory of flow, personalities could depend on social factors (Csíkszentmihályi, 1975) or education (Olson, 1999). In this research about sleep apps, social image is not a significant antecedent to adoption, due to the technology context (e.g., sleep apps are not visible to other people, and are seen as private or intimate technologies). Thereby, future research could focus on which extent social circles influence well-being and empowered personalities, and on the difference between private personalities (how people feel they are in a private context) and social personalities (how people feel they should behave with other people). Overall, sleep apps should increase the willingness to improve quality of life and well-being, enhancing positive health practices on the long term.

Then, the sample is made of French students, and the variables might vary with other cultures and generations (Straub et al., 1997; Hofstede, 2001); therefore, it should be interesting to replicate this study in other countries and representative samples to increase the empirical generalisation of results (Bianchi & Andrew, 2012; Colton et al., 2010).

Finally, we could not have real-time behavior indicators that should give interesting results regarding perceptions of well-being and real use (Ahmadpour et al., 2016). Therefore, collaborating with firms of sleep apps would enable researchers to know if sleep apps really improve sleep, well-being, and real use or if it is only a perception, due to personality traits for example.

Summary of contributions

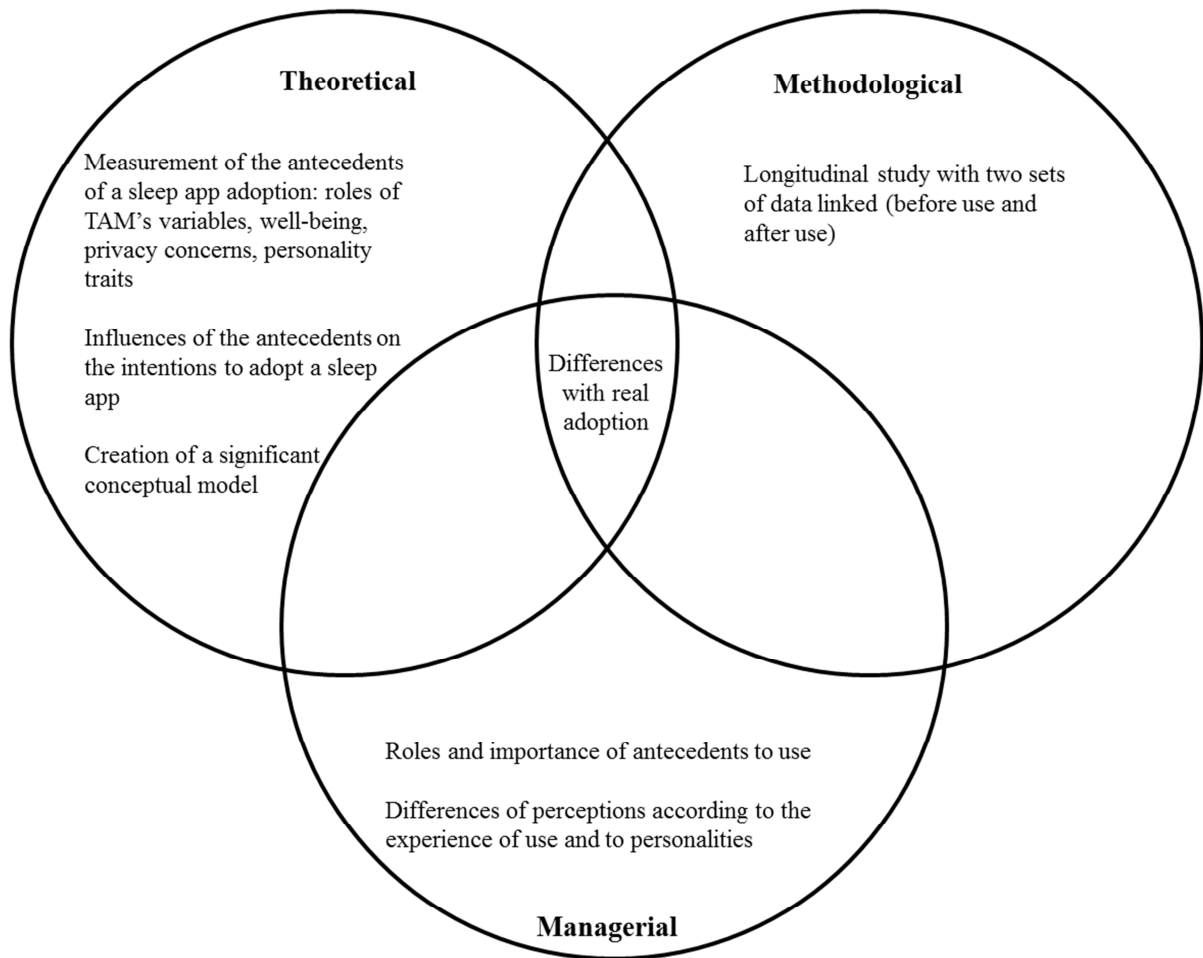


Figure 22: Summary of contributions (*Article 3; adoption of sleep apps*)

The summary of our contributions for this article 3 (Figure 22) shows three kinds contributions:

- (1) Theoretical contributions: we measure antecedents of the adoption of a sleep app, and their links between each other in order to create a significant conceptual model;
- (2) Methodological contributions: we do a longitudinal study (before use and after use) to better understand the acceptance then adoption process;
- (3) Managerial contributions: we highlight the roles and importance of different antecedents of adoption and types of personalities to help redefine managerial targeting strategies.

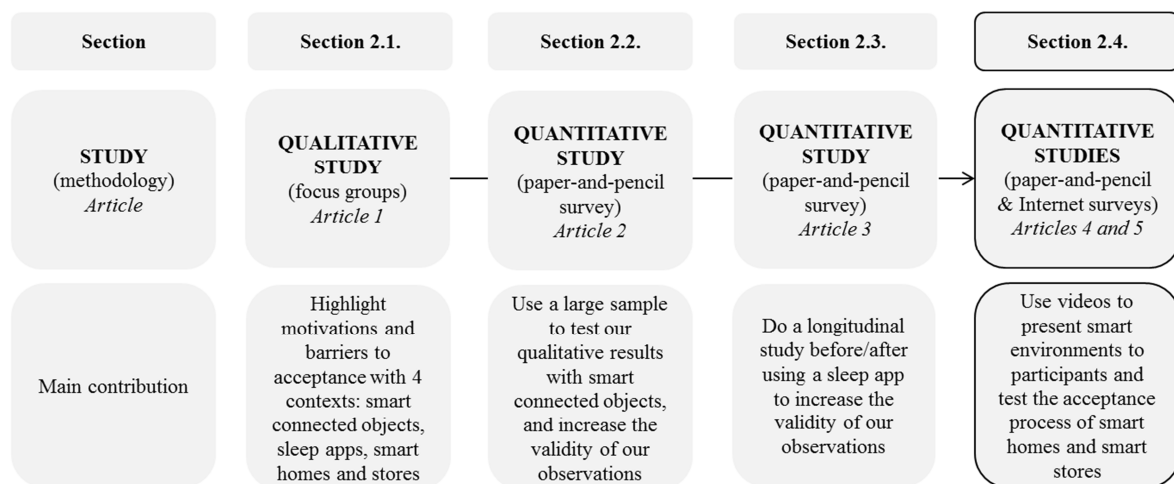
Transition: from smart apps to smart environments acceptance

This latter longitudinal study allows us to deepen the acceptance process and barriers to sleep apps before use, then the adoption process and motivations to keep on using a sleep app.

In order to improve the validity of our results, we decide to study a more global concept of the IoT: smart environments. With smart environments, consumers tend to forget about the omnipresence of these technologies while smart technologies can interfere spontaneously in people's lives, anytime and anywhere, creating unexpected behaviours (Van der Hoven, 2013). Furthermore, people tend to connect themselves to the Internet in free Wi-Fi areas, and these connections increase the quantity of data stored, which could be used without users' permissions (Van der Hoven, 2013). Thereby, with smart public or private environments, it is more difficult to control how the IoT works and how the data is used since the information flow is facilitated, and transfers are quicker and cheaper (Van der Hoven, 2013).

To study the acceptance of smart environments, we focus on two types of environments: smart homes (private environment) and smart stores (public environment). These types of environments should become more and more popular in the coming years, and should influence consumer behaviours. Note that our sample of participants has never tested these types of environments before answering to our surveys.

Therefore, in section 2.4., we perform two quantitative studies with two different contexts: smart homes, and smart stores. For both, we used videos to present these smart environments to our respondents, and then our aim was to test the acceptance process.



2.4. Smart environments acceptance

The two next articles study the antecedents of smart environments such as smart homes (*Article 4: The acceptance process of the Internet of Things: How to improve the acceptance of the IoT technology?*) and smart stores (*Article 5: Consumers' acceptance and resistance factors toward smart connected stores*) which are both part of consumer daily lives. Smart environments are defined as a place where all kinds of smart objects and sensors work non-stop to improve people's lives (e.g., technology does the hard work for people, collects, analyzes and gives them relevant information to help them and let them gain some time and energy) (Cook & Das, 2005). There are three kinds of smart environments: virtual computing environments (smart devices automatically access to smart networks and services), physical environments (smart devices, tags, sensors, and controllers present in an environment to collect the data going through networks), and human environments (people using smart devices like mobile phones, or SCO, thus creating data) (Poslad, 2009). There could also be a hybrid combination of all these environments (Poslad, 2009).

Figure 23 sums up our main objectives and methodology for our articles 4 and 5.

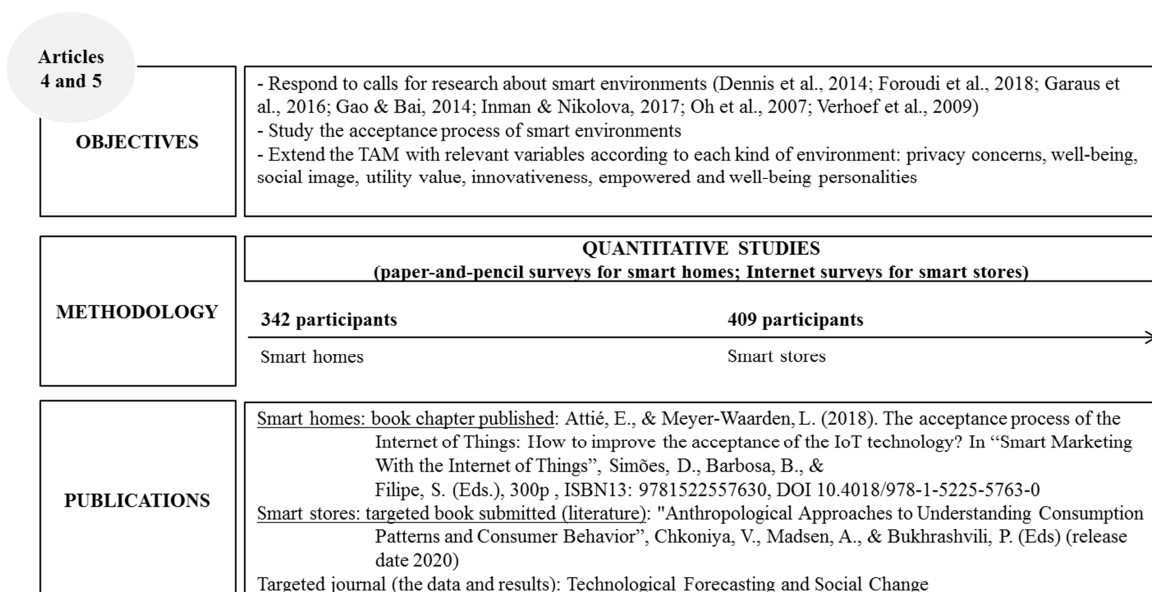


Figure 23: Main objectives and methodology (*Articles 4 and 5; acceptance of smart environments*)

2.4.1. The acceptance process of the Internet of Things: How to improve the acceptance of the IoT technology? (Article 4)

Abstract

The Internet of Things (IoT) is progressively and surely invading environments and people's daily lives, consequently creating new kinds of consumer needs and behaviours. More and more companies are getting involved in this growing field, showing the importance for them to deepen this technology market. This chapter aims to study the acceptance process of the IoT in the context of smart homes. More specifically, we test which main factors influence the acceptance of the IoT at home, such as privacy, well-being, social, and utility values. To conduct this study, 342 participants answered to paper-and-pencils surveys. The importance of each value is demonstrated, according to specific targets, and according to examples of products and services.

2.4.1.1. Introduction

The IoT should widely transform the way people live and improve quality of life (Porter & Heppelmann, 2014). Indeed, the IoT can connect everything together, dependently or independently of the initial settings pre-set by users, and can provide personalized feedback and features through mobile applications and connected object interfaces. The IoT is an interconnected environment made of invisible networks of networks that can collect, analyze and store data, and control connected objects which then interact with people or other physical or virtual things (Hoffman & Novak, 2018). Indeed, the IoT connects physical objects, such as smart watches, connected cars or connected household appliances for example, anytime and anywhere to the Internet, using wireless technology, in order to reach desired goals (e.g., sleep monitoring, sport activity, other measures of health and well-being) (Yang et al., 2013). Every object can be equipped with artificial intelligence, and therefore become 'smart' objects, to seduce technophile consumers. A smart home is equipped with sensors fixed on furniture and home equipment which are used in a home environment and supposedly, in a non-intrusive manner (Yao et al., 2018). This technology is spreading widely thanks to expanded Internet networks, high mobile adoption and low-cost sensors, but innovations can also fail due to changing demand, user reluctance, or strong competition. Thereby, it is essential for managers to understand the acceptance process of smart homes to respond to

consumer needs and ensure better profits. The main contribution of this study is to understand the acceptance of the IoT, through the context of a smart home.

Firstly, a literature review is presented in section 2.4.1.2., which is followed by the methodology in part 2.4.1.3; results are presented in section 2.4.1.4., and they are discussed in section 2.4.1.5.; then, we detail the contributions of this study in section 2.4.1.6., followed by limits and research directions in section 2.4.1.7.

2.4.1.2. Literature review

The IoT brings out benefits and risks, and reasons for consumer attraction and rejection. In this study, the main objective is to understand which variables have an influence on the acceptance process of the IoT in the context of smart homes, and subsequently give managerial recommendations.

First, a qualitative study was done with users and non-users, to study their motivations and reluctances to use the IoT in the context of smart homes (*see Article 1*). According to this preliminary analysis, we study variables that seemed to be the most relevant in the context of smart homes, and we built the links between each variable upon a literature review, so as to shape a theoretical model. Figure 24 presents this theoretical model.

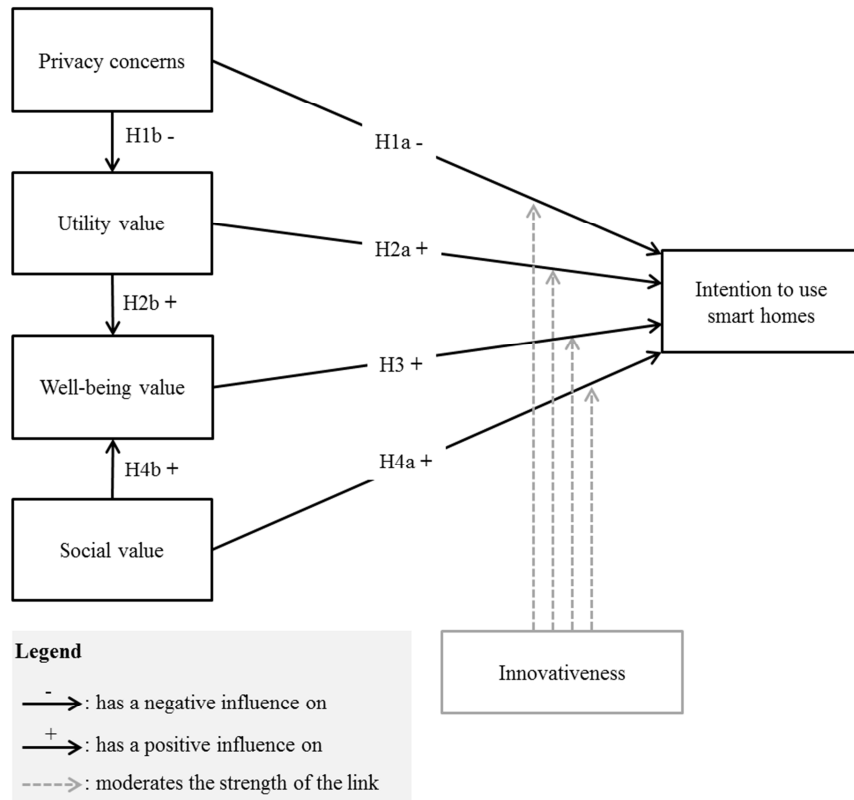


Figure 24: Conceptual model (*Article 4; acceptance of smart homes*)

Technology trust is one of the most important key variables when evaluating technology use (Hoffman et al., 1999; Song & Lee, 2012). It can be interpreted from two perspectives: the way the data is managed, and the perceived safety of the technology itself. Privacy issues and technical incidents are often spread by the media, increasing consumer doubts and fears toward innovations (e.g., Freimuth & Mettger, 1990). For example, hackers could get the financial and health data from bank applications or health trackers, and they could control applications without users noticing it. Indeed, the IoT enables to track, collect and use personal data, increasing doubts about confidentiality and safety. Thus, the data collection can be seen as intrusive, opaque and asymmetrical regarding the information (N’Goala, 2015), arousing privacy concerns (Phelps et al., 2000). Privacy concerns define how users are concerned about the flow of personal information (Shin, 2010). The more people trust the IoT (both data management and technology safety), the less they should perceive privacy concerns (Shin, 2010). These concerns diminish technology acceptance and utility value because the risks seem greater than the benefits (Dimitriadis & Kyrezis, 2010). Thereby, we hypothesize:

H1a: In the context of smart homes, privacy concerns about the IoT have a negative influence on the intention to use the IoT

H1b: In the context of smart homes, privacy concerns about the IoT have a negative influence on utility value

Furthermore, functional and utility benefits improve technology acceptance and use (Rauschnabel et al., 2015). Utility value is defined as the willingness to use the IoT to accomplish specific useful tasks (West & Turner, 2010). The IoT brings useful features by responding to primary technological needs, like communication, with smartwatches and connected speakers, for example, or like research of information with smart televisions, smart refrigerators, and other smart interfaces. Thereby, consumers who perceive the IoT as useful should be highly tempted to try the technology (e.g., Davis, 1989). Besides, the functional capacities of the IoT can help people manage their health indicators and daily life (Prayoga & Abraham, 2016), improving well-being:

H2a: The utility value of the IoT has a positive influence on the intention to use smart homes

H2b: In the context of smart homes, the utility value of the IoT has a positive influence on the well-being value

Moreover, the IoT should enhance feelings of well-being (Xia et al., 2012). Perceived well-being is defined as the positive emotion felt when a desired state is reached (Higgins, 1997). It is defined as a subjective state of fullness resulting from judgments, emotions and aspirations about the perception of a current situation, compared to a past or future of the person or entourage (Ayadi et al., 2019). Three dimensions defining well-being value are measured: (1) expected hedonism (i.e., the emotional value of a given experience enhancing feelings of enjoyment and playfulness; Grappi & Montanari, 2011), (2) health benefits (i.e., a state of well-being reached when people can use their abilities, manage stress, work productively, and make a contribution to the world; Long, 2016), and (3) quality of life (i.e., the subjective well-being, health and economic indices of an individual; Diener & Suh, 1997). Greater perceived well-being with the IoT implies greater use (e.g., Davis & Pechmann, 2013). Therefore, users expecting to feel well-being when using the IoT will be more willing to adopt smart homes:

H3: The well-being value of the IoT has a positive influence on the intention to use smart homes

According to the social cognitive theory, social value also influences technology acceptance (Venkatesh et al., 2003), and well-being (Munzel et al., 2018). Social influence guides beliefs and opinions, and mainly comes from external sources, such as co-workers, family members, friends, neighbours, the media and advertising. If consumers believe that innovations give them a positive image within their social group(s), acceptance and use are accelerated (Rogers, 1983). There is also a link between the social value and hedonism, with the experience of use (Aurier et al., 2004). The more users feel that the IoT improves their social status, the better they should feel about it and willing to adopt smart homes:

H4a: The social value of the IoT has a positive influence on the intention to use smart homes

H4b: In the context of smart homes, the social value of the IoT has a positive influence on the well-being value

Furthermore, personal characteristics, such as innovativeness, moderate the acceptance process. Studies showed that innovativeness is a moderator between perceptions and intention to use a technology (Agarwal & Prasad, 1998; Leonard-Barton & Deschamps, 1988). Innovativeness represents the willingness to try and adopt innovations (Rogers, 1995), like the IoT. Thus, innovative people should rate higher the utility, well-being, and social values than non-innovative people, who will be more bounded to privacy concerns and their consequences:

H5: The direct effects hypothesized on the intention to use smart homes in H1a, H2a, H3, and H4a are stronger when users have a higher level of innovativeness

2.4.1.3. Methodology

The sample is made of 342 respondents who did not have a smart home during year 2016–2017. Before answering to a paper-and-pencil questionnaire, they watched a short movie presenting smart homes. In the scenario, a teacher cannot give class in the morning at the last moment; therefore, the alarm clock of the students automatically calculates the best new time to wake up, taking into account the next class and bus timetables. The heater and coffee machine are resettled without any action from the students while they are still asleep.

The variables of the model are measured with existing measurement scales adapted to the context of smart homes, and which have already proved their relevance in past research, and for this study as well (Table 25). Scales reliability is suitable according to literature standards (factor loadings > .70; Anderson & Gerbing, 1988), the Cronbach α shows the reliability of the psychometric test (Cronbach α > .70; Nunnally, 1978), and the average variance extracted (AVE) shows construct reliability (AVE scores > .50; Fornell & Larcker, 1981).

Variable (adapted scale); scales reliability indicators	Factor loadings
Well-being value (Munzel et al., 2018; Howie et al., 1998; Diener et al., 1985); Mean = 2.31; Cronbach = .87; Joreskog = .99; Convergent validity = .98	
I would feel good using the IoT technology for my home	.88
Using the IoT technology in my home would make me feel happy	.85
Using the IoT would be a fun distraction	.86
By using a smart home, I would definitely increase my quality of life	.88
I would feel better if I use the IoT technology in my home	.87
Mean	.87
Intention to use smart homes (Venkatesh & Davis, 1996); Mean = 2.89; Cronbach = .82; Joreskog = .94; Convergent validity = .74	
Considering the benefits of the IoT, I intend to use it in my home	.89
If I have access to the IoT, I really intend to use it for my home	.89
In the future, my time spent using the IoT will increase in my home	.86
Mean	.88
Social value (Sweeney & Soutar, 2011); Mean = 1.63; Cronbach = .88; Joreskog = .99; Convergent validity = .99	
A smart home would give me a more acceptable image	.85
A smart home would improve the way I am perceived	.86
A smart home would give a good impression of me to my relatives	.88
A smart home would give me better social approval	.87
Mean	.86

Variable (adapted scale); scales reliability indicators	Factor loadings
Utility value (Arnold & Reynolds, 2003); Mean = 2.63; Cronbach = .86; Joreskog = .97; Convergent validity = .81	
A smart home would help me in my daily life	.81
A smart home would help me achieve my tasks faster and save time	.86
A smart home would make my life easier	.85
A smart home would be very useful to me	.83
Mean	.84
Privacy concerns (Hong & Thong, 2013); Mean = 3.41; Cronbach = .80; Joreskog = .93; Convergent validity = .75	
It bothers me if a smart home collects my information	.91
I am worried about the information a smart home could get about me	.89
It bothers me to not control the information a smart home gets from me	.90
Mean	.90
Innovativeness (Faurie & Van de Leemput, 2007); Mean = 2.61; Cronbach = .79; Joreskog = .91; Convergent validity = .82	
If I hear about a new technology, I like to try it	.83
I am usually the first one to use a new technology in my entourage	.85
I feel able to use a new technology by myself	.86
Mean	.85

Table 25: Scales reliability indicators (*Article 4; acceptance of smart homes*)

Then, the discriminant validity of the constructs is tested. Table 26 is a matrix that shows the correlation between variables, and average variance extracted values on the diagonal. According to Fornell and Larcker (1981), discriminant validity is significant when the average variance extracted is higher than the value of correlation coefficients on corresponding row and column.

	IU	Privacy	Utility value	Well-being	Social value
IU	.82				
Privacy	-.21**	.76			
Utility value	.35***	.10***	.81		
Well-being	.19***	.01*	.23***	.86	
Social value	.11***	.01*	.08*	.07**	.78

***=*p*-value<.001; **=*p*-value<.01; *=*p*-value<.1; IU stands for intention to use, privacy for privacy concerns, well-being for well-being value

Table 26: Discriminant validity table (*Article 4; acceptance of smart homes*)

Table 26 indicates that the average variance extracted values are above 0.5 and above the correlation coefficients for each variable. The cross-factor loadings of each variable also exceed the factor loadings of the other variables, showing discriminant validity between all the variables of the model (Fornell & Larcker, 1981).

2.4.1.4. Results

In line with literature, gender is a control variable to provide a stronger test of the hypotheses (Gefen & Straub, 1997; Venkatesh & Morris, 2000). Following longstanding and cultural clichés, men are said to be more attracted to useful features and are considered as more technology experts than women, who are more attracted to well-being and health benefits (Venkatesh & Morris, 2000). Table 27 shows the indicators for the control variables tests.

	R²	ΔR²	F (sig)
Without control variables	.55		
With gender	.55	0	8.11 (.04)

Table 27: Control variable indicators (*Article 4; acceptance of smart homes*)

Table 27 indicates that gender is not a significant predictor of the model.

Then, the data is analyzed using structural equation modelling with Analysis of Moment Structures from Statistical Package for the Social Sciences (Amos 21 from SPSS). The estimated direct path coefficients are reported in Table 28. We choose Amos because the multivariate normality analysis is acceptable (Appendix 5A), the sample size is about 200 observations and we want to confirm theoretically assumed relationships (theory and conceptual framework section).

Dependent variable	Independent variable	Hypothesis	β coefficient	t-value
Intention to use R ² = .55	Privacy concerns	H1a	-.21**	6.55***
	Utility value	H2a	.35***	3.44***
	Well-being value	H3	.41***	3.23***
	Social value	H4a	.23***	5.56***
Utility value R ² = .11	Privacy concerns	H1b	-.08**	4.32***
Well-being value R ² = .35	Utility value	H2b	.13***	8.51***
	Social value	H4b	.12***	7.65***

*** indicates p -value < .001; ** p -value < .01; * p -value < .1; ns = non-significant.

Table 28: Results of the estimated direct path coefficients (*Article 4; acceptance of smart homes*)

Table 28 indicates that privacy concerns, utility value, well-being value and social value explain 55% of the variance of IU; privacy concerns explain 8% of the variance of the utility value; utility value and social value both explain 35% of the variance of the well-being value. Further, privacy concerns have a negative influence on IU ($\beta = -.21^{**}$); H1a is supported. Moreover, the utility value, well-being value, and social value have a positive influence on IU (respectively $\beta = .35^{***}$; $\beta = .41^{***}$; $\beta = .23^{***}$); H2a, H3 and H4b are supported. Then, privacy concerns have a negative influence on the utility value ($\beta = -.08^{**}$); H1b is supported. Finally, utility value and social value both have a positive influence on the well-being value (respectively $\beta = .13^{***}$; $\beta = .12^{***}$); H2b and H4a are supported.

Moreover, the model fit indicators are acceptable ($\text{Chi}^2/\text{DF} < 5$ (Byrne, 2006), $\text{RMSEA} < .08$ (Browne & Cudeck, 1993), $\text{CFI} > .80$ (Bentler, 1990), $\text{TLI} > .80$ (Bentler & Bonett, 1980)) (see Figure 25).

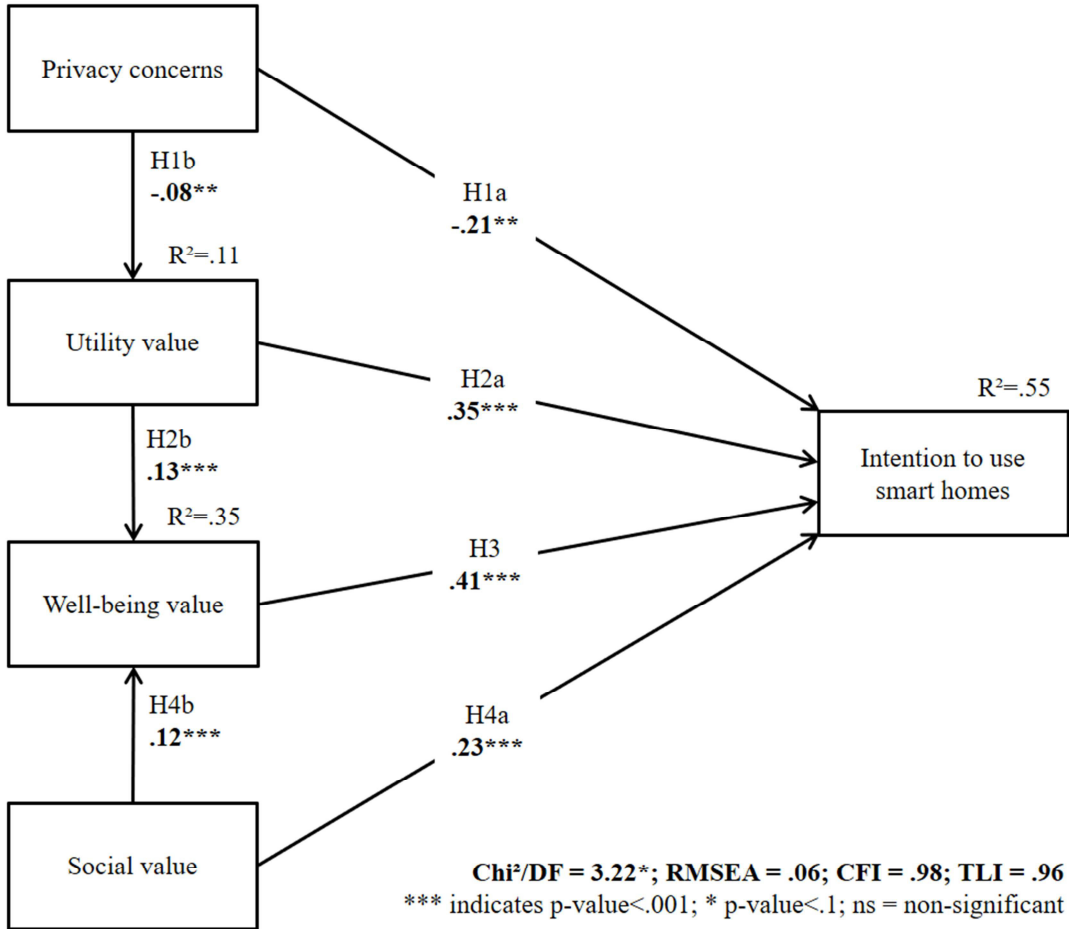


Figure 25: Conceptual model and model fit indicators (Article 4; acceptance of smart environments)

Finally, we use Process Model 1 (Hayes, 2012) to test the moderating effect of innovativeness. See Appendix 5B for the details. Results show that innovativeness positively moderates the influence of utility value, well-being and social value on IU (respectively $\Delta R^2 = 2\%$; $\Delta R^2 = 1\%$; $\Delta R^2 = 1\%$); H9 is partly supported.

2.4.1.5. Discussion

Results show that utility, well-being and social values positively influence the intention to use smart homes. These results show that consumers are looking for different aspects: rational with utility, emotional with feelings of well-being, and social aspects. This result can be explained by the fact that the IoT is a cognitive technology (i.e., technology that uses the technical capabilities of users). It appears that consumers tend to use the IoT as long as it gives them a rational way to justify its use with useful features (Huh & Kim, 2008), and if it improves senses of well-being as well (Bruner & Kumar, 2005; Childers et al., 2001). Literature showed that consumers are more likely to adopt a technology if it is useful (Saga & Zmud, 1994). The influence of the well-being value is stronger than the value value on IU, as in the literature (Adams et al., 1992; Bertrand & Bouchard, 2008; Bruner & Kumar, 2005; Childers et al., 2001; Hu et al., 1999). This difference can be explained by the fact that hedonic technologies imply a greater well-being value (Childers et al., 2001). We thus follow another stream of literature saying that utility is the first most important antecedent of acceptance, followed by well-being (Childers et al., 2001; Davis, 1989; Davis et al., 1989, 1992). Thus, technology can create positive experiences and well-being, leading to greater acceptance (Andreasen et al., 2012; Davis & Pechmann, 2013).

Further, consumers will be prompted to try and use the IoT in the context of smart homes if the use is in agreement with the social image they seek within their social group(s), as in the literature (Muk & Chung, 2005). Literature showed that even if users do not feel well-being with a technology, they could adopt this technology if it improves their social status and image (Saga & Zmud, 1994).

However, privacy concerns negatively influence the intention to adopt smart homes: the more users are concerned about the management of their data flow, the less they intend to use the IoT (Connolly & Bannister, 2007). The way the IoT is able to track and get personal information represents the major reason for rejection of the IoT (Buchanan & Ess, 2006). A higher utility value with personalization services improves positive experiences and lowers

privacy concerns (e.g., Dimitriadis & Kyrezis, 2010; Sirdeshmukh et al., 2002; Xu et al., 2011). Moreover, according to the theory of the privacy calculus, personalized services can justify the collection of personal data (Awad & Krishnan, 2006).

Nevertheless, consumers are heterogeneous, and different types of IoT users should be considered to refine marketing strategies. As expected, innovative people expect more benefits and positive beliefs about the IoT (Agarwal & Prasad, 1998; Leonard-Barton & Deschamps, 1988; Mittal & Kamakura, 2001; Reinhardt & Gurtner, 2014). In line with literature, we confirm the importance of using innovativeness as a moderator of the acceptance of technology (Yi et al., 2006).

2.4.1.6. Contributions

2.4.1.6.1. Theoretical contributions

This research brings out new insights for the acceptance of smart homes in marketing literature that still lacks to explain factors of the acceptance of smart environments (Verhoef et al., 2017). More precisely, we build a theoretical model with relevant variables, such as privacy concerns, utility value, well-being value and social value. We show that utility value is the first antecedent of acceptance, followed by well-being value, then social value, and privacy concerns. Results also demonstrate that innovativeness moderates the links influencing the acceptance of the IoT, in the context of smart homes. The IoT should first attract innovators (von Hippel, 1986): they need to perceive innovations as useful, intuitive, easy to use, and hedonic to judge them as ‘good’. Once convinced, innovators will do relevant word-of-mouth contact, as their entourage sees them as experts. Each consumer is more or less an innovator, favouring one or two values, and is attracted to specific kinds of IoT technologies.

2.4.1.6.2. Managerial contributions

This study shows that the main reticences of acceptance are privacy concerns. Tags and sensors can track and collect personal data, then send it to data centres. The data is analyzed to do personalized features, marketing research and/or be sold to other companies. Technology can also be hacked and the data can be used for unknown reasons, showing the importance of safety regarding data management. Numerical information makes consumers

more sensitive (Laporte & Laurent, 2015). Firms must be transparent regarding data policies and can focus on social indicators (age, gender, religion), technical parameters (privacy settings, regular safety controls, software, networks equipment) and legal solutions (laws and regulations, ethics and moral policies). Even if privacy risks limit the acceptance of the IoT, benefits of personalization can be higher than the perceived privacy loss (Xu et al., 2011). Perceived privacy risks can also be decreased by increasing control and personal knowledge to users (Armitage & Conner, 1999; Awad & Krishnan, 2006; Azjen & Driver, 1991; Kirsch, 1996). Thus, privacy policies should be clear and understandable, protecting users' data. Trust directly influences service usage and purchase, showing its importance in service relationship development (Aurier & N'Goala, 2010). Further, companies could reward users according to the quality of the data (the more valuable information given, the more rewards, such as discounts, exclusive offers, digital coupons, small gifts, personalized features, or thank you cards). Rewarding consumers should increase their willingness to give private data, as well as satisfaction and loyalty of use. For example, the company Foursquare sends collectible stickers, pins or items to thank its users. It motivates people to collect more giveaways by using the app and giving personal data, which improves the user database. Therefore, sport connected devices could collaborate with sport events, and according to the data collected, reward users. These kinds of interactions must be regular, and companies should stay in touch with consumers during the whole experience to increase loyalty of use. However, companies should favour attractive unique prizes rather than offering many same prizes in order to attract more participants (Laporte & Laurent, 2015).

2.4.1.7. Limits and further research directions

This study uses the perceptions and intentions of respondents, and not actual behaviours. Collaborating with IoT companies could be a good way to analyze real use and behaviour, highlighting the way the values evolve (Ashraf et al., 2014; Davis et al., 1989; Keil et al., 1995). It could also be interesting to examine behavioural loyalty and usage indicators to study the IoT adoption on the long term in the context of smart homes.

Besides, the sample comes principally from France and the Y generation, making it hard to generalize the results. Additional work could improve the survey by increasing the number of respondents with other countries (Straub et al., 1997) and other generations (Bianchi & Andrew, 2012; Colton et al., 2010).

Furthermore, the technology adoption theory suggests studying other relevant variables that are not tested in this study, such as perceived self-congruity, or perceived price-to-quality ratio (Gefen et al., 2003).

Emerging trends show that the IoT is invading consumer daily life. An interesting research domain is the communication through smart objects. Once consumers accept to use smart objects, these objects track and analyze their personal information, and companies have the ability to resell this information. It would be interesting to see to which extent users are ready to share personal information for personalized advertising purposes with, for example, smart watches or smart televisions. Moreover, further research could test to which extent these results could be applied to other specific contexts of study, like smart stores, smart cities, smart stadiums, smart airports, etc., as the IoT has no limit to connect places. Thereby, new questions emerge and could then be studied: how do consumers react when they do not necessarily choose how the IoT influences their daily lives in public places? How does the acceptance process evolve versus private places?

Finally, from a medical point of view, research has shown that health risks, defined as the extent to which a user believes that using the IoT should have negative consequences on health, negatively influence IoT trust and acceptance (Stock et al., 2016). Popular media have reported a lot on the potential health risks associated with the use of the Internet radiations that can cause illnesses, such as cancers (Myung et al., 2009), increasing consumer awareness. Even if smart objects are said to have few or no direct impacts on health due to very low electro radiations, it should be very interesting to study the actual impact of the regular accumulation of these low electro radiations on people.

Summary of contributions

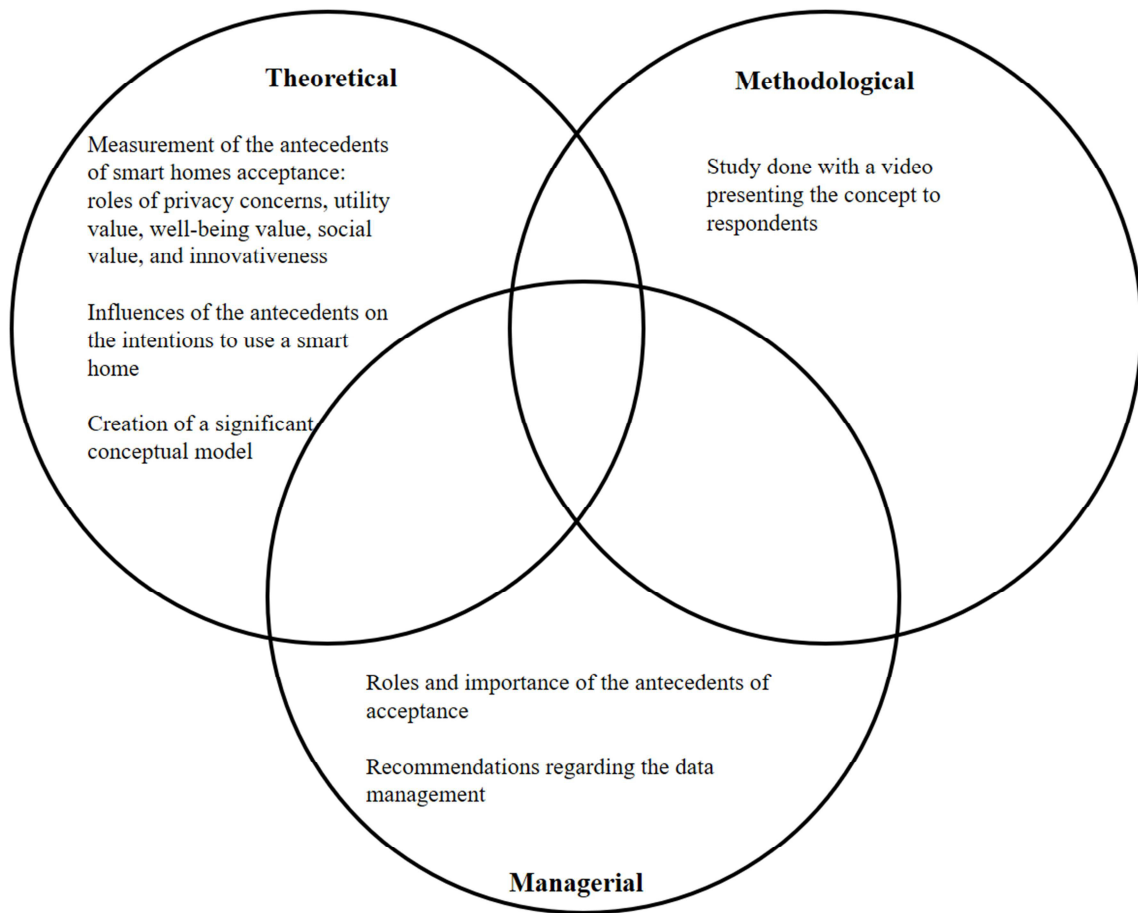


Figure 26: Summary of contributions (*Article 4; acceptance of smart homes*)

If we sum up our main contributions, Figure 26 shows that there are three main contributions:

- (1) Theoretical contributions: we highlight the roles of antecedents of the acceptance of smart homes to construct a theoretical model with privacy concerns, utility value, well-being value, social value, and innovativeness;
- (2) Methodological contributions: we show our respondents a video to present the concept of smart homes, in order to increase the understanding of our survey;
- (3) Managerial contributions: we show the importance of each antecedent in order to improve the acceptance process.

Transition: from smart homes to smart stores

To study the acceptance of an IoT environment such as smart homes enables us to deepen our knowledge on the IoT and smart technologies adoption. Moreover, in order to improve external validity, we reproduce this study with another IoT context: smart stores. Smart homes remain in the private sector whereas smart stores are in a public sector. Besides, smart stores are becoming a highly interesting topic for managers who still wonder whether they should take the plunge (and risks) and transform their store into a smart store. As consumer demand is evolving, research is highly interested in the perceptions of consumers toward smart environments such as smart stores (Foroudi et al., 2018; Verhoef et al., 2017). For example, in the US, Amazon opened its first connected store in 2018, called AmazonGO. In this store, there is no cashier and waiting line because the entire purchase path is automated. Consumers only need to have an account on the AmazonGO mobile app to enter the store via connected turnstiles. In the store, thousands of sensors, and cameras on the ceiling, analyze the products purchased in real-time and register the price. When consumers have finished their purchase, they simply pass through turnstiles equipped with sensors and their bank account is automatically debited when they leave the store. Based on a similar idea, Casino Group also opened their store of the future in Paris in 2018. This store is opened 24 hours a day. During the day, it is accessible to all customers, but from 10 P.M. and all night long, consumers need the Casino Max mobile app to enter the store. Then, the system of purchase is the same as AmazonGO: no cashier, no waiting line. The group also offers voice recognition kiosks, connected mirrors, touch-sensitive digital walls, and interactive labels to improve fun and senses of hedonism.

***2.4.2. Consumers' acceptance and resistance factors toward smart connected stores
(Article 5)***

Abstract

The IoT and smart technologies enable a better knowledge of consumers' needs while improving sales conditions (e.g., easier access to information and products, gain of time, smart entertaining environments, analysis of real-time consumption data, etc.). However, implementing a smart system in a store is an important financial investment. Thus, it is necessary for managers to understand consumers' expectations toward smart connected stores, and the perceived benefits and risks, in order to evaluate the opportunities for store managers. As empirical studies are missing on the topic, this research contributes to theory by developing a theoretical model for explaining and predicting consumers' acceptance process of smart connected stores. 409 respondents watched a video showing a smart retail store before answering an online survey. Few investigated factors of consumer acceptance and resistance are taken into account, namely social image, consumer well-being and privacy concerns. Innovativeness and four types of personalities moderate the acceptance model, giving managers useful insights for strategy development, targeting, and communication.

2.4.2.1. Introduction

The Internet of Things (IoT) and smart technologies considerably influence the retail industry and customer shopping experiences (Inman & Nikolova, 2017; Manyika et al., 2013; N'Goala, 2016; Renko & Druzijanic, 2014). Strategies now extend product displays to fully immersive retail stores. In France, managers and consumers are witnessing a timely metamorphosis of the point of sale (i.e., smart mirrors in fitting room so that consumers can virtually try on clothes, create outfits from the inventory, request matching products and connect to social networks). For example, Decathlon, a French store specialized in sports, digitalized a store in Paris to improve consumer experience (e.g., real-time product information and inventory consultation, store transformed into a fitness room with coaches/salespeople). Moreover, the brand Bonobo ensures its consumers to find their clothing size thanks to real-time stock information. Another example is with the brand Nike which launched digital stores with touch pads to pay for products, wall screens to consult the catalogue, emails or QR codes to memorize a product, and smartphones to test the Nike mobile app. Indeed, smart retail technologies give managers tools to enhance consumer experience and service personalization (Toch et al., 2012). Smart retail stores therefore seem to be a valuable way to create greater benefits, customer loyalty, and personalized interactions on the long term (Pantano & Timmermans, 2014; Wunderlich et al., 2013). Consequently, retailers are aware of the IoT potential and are interested to use smart technologies in retailing strategies (Foroudi et al., 2018).

Smart connected stores are interactive retail systems delivering services for consumers and employees through a network of smart devices. These connected devices sense their surroundings and engage in real-time data collection, interaction, and feedback (Wuenderlich et al., 2015). Engineering researchers also talk about physical Internet stores that use networking technology, wireless, and cloud manufacturing, to upgrade traditional retail industries into smart stores (Montreuil et al., 2012). Therefore, the IoT is leading the retail industry to more digitalized in-store interactions with consumers and personalized shopping experiences (Barthel et al., 2015; Immonen & Sintonen, 2015; Roy et al., 2016; Xu et al., 2011). This involves consumers' cognitive, affective, emotional, social, and physical responses to retailers (Verhoef et al., 2009). Investments in smart connected stores are predicted to reach \$36 billion by 2020 (Research and Markets, 2015). Thus, in a high and

growing competitive market, smart connected stores seem to be a promising tool to reduce customer churns by offering personalized in-store experiences (Kim et al., 2017).

Due to the development of smart stores in France and as empirical studies on the topic are missing, there are many calls for research about these kinds of smart environments (Dennis et al., 2014; Foroudi et al., 2018; Gao & Bai, 2014; Garaus et al., 2016; Inman & Nikolova, 2017; Oh et al., 2007; Verhoef et al., 2009). Therefore, it becomes of high academic and managerial relevance to understand how the IoT is shaping the future of retailing (Kotler et al., 2017). Consequently, this research contributes to theory and practice by developing a theoretical model explaining consumers' acceptance of smart retail stores and buying intentions. To do this, few investigated factors of consumer technology acceptance and resistance are simultaneously taken into account, namely perceived social image, perceived well-being, and privacy concerns (as little research has investigated customer resistance of technology innovations; Laukkanen, 2016; Talke & Heidenreich, 2014). Resistance can take three forms: rejection (consumers may not adopt the technology), postponing (the context is not suitable for adoption), or opposition (consumers act to resist to the technology) (Szmigin & Foxall, 1998). Hence, understanding the factors of resistance is important for the success of smart products (Kleijnen et al., 2005).

Then, this study extends existing theory on individual consumer differences by deepening the roles of consumer traits like innovativeness, empowered and well-being personalities (e.g., Gelderman et al., 2011; Venkatesh & Bala, 2008).

This article is organized as follows: the next section 2.4.2.2. shows the literature review, conceptual framework, and hypotheses; this is followed by the methodology and data used in section 2.4.2.3.; then in section 2.4.2.4., the results of the study are stated, followed by a discussion in section 2.4.2.5., and by contributions to research and practice in section 2.4.2.6.; finally, the limits of this study and future research directions are presented in the last section 2.4.2.7.

2.4.2.2. Literature review

The IoT enables personalized offers, and responds to consumer needs of innovation, self-awareness and well-being. However, the IoT is also a source of concerns that can lead to rejection toward the technology. This next part aims to define the main acceptance and resistance factors of smart retail stores.

The theoretical model (Figure 27) is built upon the factors influencing the intention to visit smart retail stores and intention to buy, namely privacy concerns, perceived well-being, perceived social image, innovativeness, and consumers' personalities. It refers to the social cognitive theory (Bandura, 1986) which states that socioenvironmental, personal, and behavioural factors are key determinants of consumer behaviour.

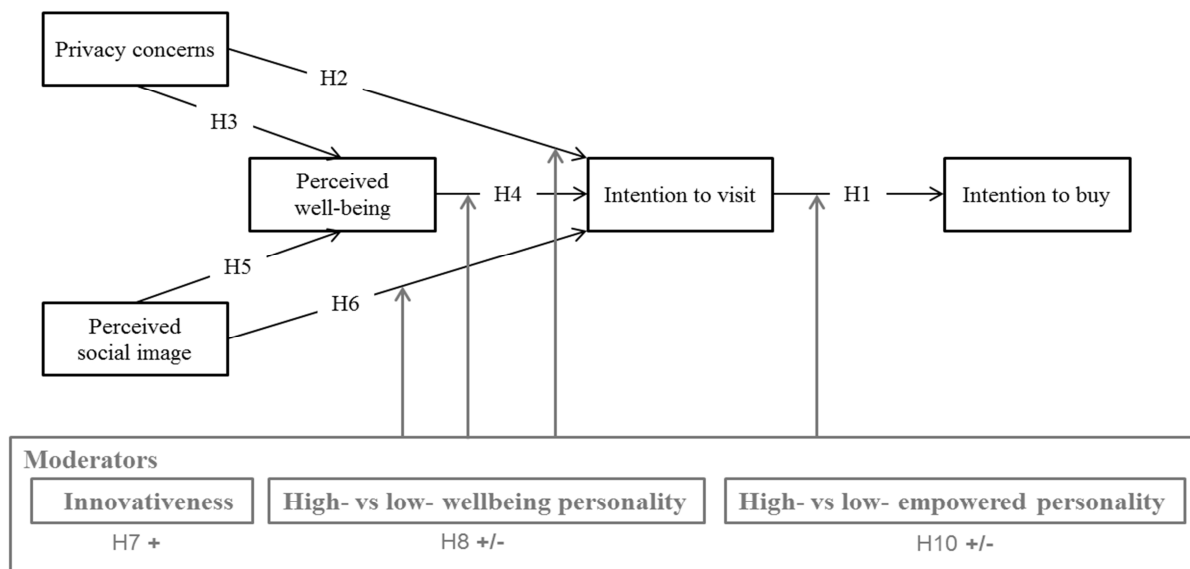


Figure 27: Conceptual model (Article 5; acceptance of smart connected stores)

IoT technologies should influence consumer behaviours and perceptions (Sivarajah et al., 2015), including toward smart retail stores (Foroudi et al., 2018). Consumers should be more willing to buy in a smart retail store when they have positive attitudes toward the brand and technology (Foroudi et al., 2018; Ngo & O'Cass, 2013). Indeed, behavioural intentions to buy are also linked to brand images (Laroche & Brisoux, 1989; Laroche & Sadokierski, 1994; Teng & Laroche, 2007). Thus, as behavioural intentions are strong predictors of actual behaviours (Ajzen, 1991; Sheppard et al., 1988), we hypothesize:

H1: The intention to visit smart retail stores positively influences consumers' intentions to buy

Each shopping experience can be analyzed in real time as smart devices connect themselves to the Internet automatically to collect consumer data (i.e., purchases, geolocation, reviews on social media, smart connected objects data). This aims at improving the store efficiency, accuracy and economic benefits, in addition to reducing retailers' interventions. According to consumers' characteristics, the IoT is able to define the best personalized offer for them at the right time (i.e., send a personalized offer for shoes when the clients are in the shoes' department). Furthermore, smart retail stores acceptance depends on the trust consumers have into data management (Hoffman et al., 1999). The way the IoT collects real-time data can be seen as intrusive, arousing privacy concerns (Awad & Krishnan, 2006; Hong & Thong, 2013; Phelps et al., 2001). Privacy refers to consumers' perceived abilities to control disclosure and subsequent uses of their data (Milne & Culnan, 2004; Phelps et al., 2000; Westin, 1967); and, privacy concerns is defined by which extent consumers are concerned about the flow (collection and usage) of their personal information (Phelps et al., 2000). Indeed, the data collection can be quite opaque for users (N'Goala 2015). Companies collecting the data ensure that the data collection is anonymous and that there is no historic follow up of the customers (except for the data linked to loyalty programs). The IoT system takes into account only the gender, age, and purchase path. These processes should be visible to consumers to ensure transparency and trust (Portes et al., 2016). Since May 2018, the European Data Protection Regulation regulates the data market. Little research has investigated privacy concerns in the context of smart connected environments yet (Fox & Royne, 2018; Verhoef et al., 2017). These concerns generally negatively affect the acceptance process (Wüenderlich et al., 2015), decreasing the intention to visit smart retail stores. Thus, we hypothesize:

H2: Privacy concerns about data collection negatively influence the intention to visit smart retail stores

Besides, privacy concerns engender negative perceptions about smart technologies (Wüenderlich et al., 2015). Users subsequently might experience stress that decreases feelings of well-being experienced in smart retail stores (Shin, 2010; Van der Heijden, 2004; Wüenderlich et al., 2015). Research focuses more and more on this concept of well-being (Su et al., 2014). It defines how and why consumers perceive experiences in positive ways, through cognitive judgments and affective reactions, without objective facts (Diener, 1984). Consequently, quality of life and hedonism are close-related concepts included in the broader concept of well-being (Ayadi et al., 2017; Costa & McCrae, 1980; Dolan et al., 2008; Hsee et

al., 2009). In the context of smart retail stores, perceived well-being represents consumers' global judgment of how smart retail stores influence their satisfaction in their consumer, social, leisure, and community lives, which should all significantly improve their overall quality of life (El Hedhli et al., 2013). Thus, perceived well-being focuses on the emotional and hedonic benefits of performing a specific behaviour (Dabholkar, 1996). Following this stream of research, perceived well-being is operationalized in the present article as hedonism (e.g., feelings of happiness and enjoyment; Van der Heijden, 2004), quality of life (e.g., a business process that plans, prices, promotes, and distributes economic goods to consumers by maximizing acquisition, possession, consumption, maintenance; Diener et al., 1985), and satisfaction (consumers' evaluation of a product or service in terms of whether that product or service has met their needs and expectations; Bitner & Zeithmal, 2003). Therefore, we hypothesize:

H3: Privacy concerns negatively influence the perceived well-being in smart retail stores

Furthermore, perceived well-being is linked to consumer choices (Gilovich et al., 2015) and is also an antecedent of technology acceptance (Bruner & Kumar, 2005; Çelik & Yılmaz, 2011; Chiu et al., 2014; Dabholkar & Bagozzi, 2002; Hirschman & Holbrook, 1982; Johar & Awalluddin, 2011; Kim & Forsythe, 2008; Kulviwat et al., 2007; Sherman et al., 2001; Van der Heijden, 2004). Indeed, consumer well-being can come from perceived enjoyable experiences (Ryan & Deci, 2001). Consequently, hedonic experiences bring greater well-being than acquiring material possessions (Ayadi et al., 2017; Van Boven & Gilovich, 2003). The shopping experience in a physical store can combine the ease of an online transaction with the simple pleasure and social interactions of shopping. For example, a virtual assistant might help consumers and retailers to select and locate items in the store on a smartphone or from a store tablet; the digital virtual assistant interacts via a voice interface (i.e., Siri), suggests items or ensembles to upsell alternative sizes or colors, and allows consumers to request other products, sizes or colors from the virtual fitting room. Perceived well-being thus comes from the anticipated positive emotions from experiences (Perugini & Bagozzi, 2001). In turn, these perceived emotions positively influence behavioural intentions (Andreasen et al., 2012; Curran & Meuter, 2007; Dabholkar & Bagozzi, 2002; Davis & Pechmann, 2013; Koufaris, 2002; Perugini & Bagozzi, 2001; Weijters et al., 2007). So, we hypothesize:

H4: Perceived well-being in smart retail stores positively influences their intention to visit

Also, consumer well-being can be experienced with activities improving social satisfaction (Naci & Ioannidis, 2015). Perceived social image is defined as the visible and perceived inputs used to enhance a social status and image within a specific social group (Moore & Benbasat, 1991). There is a link between the social value and hedonism, with the experience of use (Aurier et al., 2004). More precisely, a positive social image has positive effects on well-being (Hoffman, 2012; Kuisma et al., 2007). Therefore, the more consumers believe that smart retail stores can enhance their social image, the more their perceived well-being should consequently increase. Thus, we hypothesize:

H5: Perceived social image by shopping in smart retail stores positively influences perceived well-being

Moreover, research has shown that social image positively influences consumer acceptance (Bandura, 1986; Compeau & Higgins, 1995; Foroudi et al., 2018; Venkatesh & Davis, 2000). Consumers who perceive smart retail stores as conforming socially are more likely to visit them (Kaul, 2005). Indeed, a behaviour that is consistent with group norms allows people to enhance their perceived social image (Kiesler & Kiesler, 1969; Pfeffer, 1981), increasing acceptance. Therefore, we hypothesize:

H6: Perceived social image by shopping in smart retail stores positively influences the intention to visit

Furthermore, people may react differently to innovations due to personality traits such as innovativeness, which is the degree of attraction toward innovations (Rogers, 1983). Innovativeness is said to be a relevant moderator of new technology acceptance models (Agarwal & Prasad, 1998; Mittal & Kamakura, 2001) as innovative consumers are more likely to accept smart environments than others (Agarwal & Karahanna, 2000). Thus, we hypothesize:

H7: Consumer innovativeness is a moderator influencing positively the intentions to visit and to buy in smart retail stores

Besides, other personality traits, such as well-being and empowered personalities, can influence the acceptance of smart retail stores.

High-wellbeing consumers are defined as autotelic people with an emotional intelligence, and feelings readily expressed (Csíkszentmihályi, 1975), who are predisposed to feel, accept and share feelings of hedonism (Attíé & Meyer-Waarden, 2018). They favour group activities, social interactions and social environments (Hock, 1962). Positive emotions, entertainment and well-being benefits lead their choices (Ryan & Deci, 2001). Therefore, these consumers use technology as a way to experience well-being (Seligman, 2011) and smart retail stores could be a way to feel expected positive emotions. On the opposite, low-wellbeing consumers are people less predisposed to accept, feel and share senses of well-being than the average people (Attíé & Meyer-Waarden, 2018). They privilege utilitarian benefits than hedonism when making choices (Harris & Westin, 1991). These consumers own a natural prudence and inform themselves before accepting new things (e.g., Mill, 2012) so the acceptance process might be longer. Consequently, the opinions of their entourage influence strongly their decisions. As smart retail stores are not well developed yet, they might not feel confident about visiting this kind of new and still unknown stores. Therefore, we hypothesize:

H8: A high —versus low— well-being consumers is a moderator influencing positively —versus negatively— the intentions to visit and to buy in smart retail stores

Then, high-empowered consumers are people predisposed to get, feel, then use senses of power over themselves, other people, companies or situations (Attíé & Meyer-Waarden, 2018; Cases, 2017). High-empowered people tend to be self-confident (Hock, 1962) and should look for improving their social status. Smart retail stores should improve their perceived social status by giving them an innovative image. On the other hand, low-empowered consumers are people not predisposed to feel, get, and therefore use power, and consequently should be less attracted to the benefits of smart retail stores. Privacy is the most important value to them so they tend to reject personalization benefits to protect personal information (Attíé & Meyer-Waarden, 2018). They are rather rational and wise (Hock, 1962). Therefore, they inform themselves about any eventual issues (e.g., health impacts, technical problems, privacy issues) before accepting new technologies (Mill, 2012). The acceptance process of low-empowered people should be longer, as for low well-being consumers. Thus, we hypothesize:

H9: A high —versus low— empowered consumers is a moderator positively —versus negatively— influencing the intentions to visit and to buy in smart retail stores

2.4.2.3. Methodology

409 French respondents answered to an online survey in France during year 2017-2018 (63% women; 32% < 21 years; 57% 22-29 years; 11% > 30 years; Mean age = 28.46). Before answering to the survey, respondents watched a one-minute video presenting a smart retail store that sells clothes. In the video, a man choose clothes to try on thanks to real-time information accessed from his phone, brings the clothes to the fitting room which displays an interactive mirror that allows him to have access to additional information about the product, as well as to ask the seller to bring him a different size or colour without having to leave the fitting room.

Constructs are measured with existing Likert scales ranging from 1 (strongly disagree) to 5 (strongly agree) and adapted to the context of smart retail stores. The confirmatory factorial analysis (see Table 29) shows acceptable reliability indicators according to the literature (Fornell & Larcker, 1981) with Cronbach α close to .70 (Nunnally, 1978), and average variance extracted (AVE) scores above .50; Fornell & Larcker, 1981); Kurtosis and Skewness tests (Appendix 6A) also indicate a normal distribution of the data (Moors, 1986). Finally, the sample size has a satisfying representativeness compared to the number of items used (Hinkin, 1995). To validate the scales and keep or discard items, factor loadings and mean by variable shows how much a factor explains a variable (factor loadings > .70; Anderson & Gerbing, 1988). These scales show a good reliability and validity in the context of smart retail stores. The final items by scale and reliability indicators are presented in Table 29.

Variable (adapted scale); scales reliability indicators	Factor loadings
Intention to buy (Chau, 1996); Mean = 2.66; Cronbach α = .86; AVE = .78	
I would appreciate the idea to regularly buy in smart retail stores	.88
I think I will buy more and more in smart retail stores in the future	.88
I think I might buy more products in smart retail stores	.87
Mean	.88
Intention to visit (Davis, 1989); Mean = 3.21; Cronbach α = .86; AVE = .88	
Smart retail stores seem like a good opportunity	.94
Smart retail stores would ensure an attractive everyday environment	.93
Considering the advantages of smart retail stores, I intend to visit one	.94
Mean	.94

Variable (adapted scale); scales reliability indicators	Factor loadings
Perceived well-being (Munzel et al., 2018); Mean = 2.97; Cronbach α = .88; AVE = .73	
I would feel well to shop in smart retail stores	.83
Shopping in smart retail stores would make me happy	.86
Shopping in smart retail stores would increase my quality of life	.86
Shopping in smart retail stores would be a fun distraction	.84
Shopping in smart retail stores would make shopping more entertaining	.81
Smart retail stores would create pleasant distractions and surprises	.79
Mean	.83
Perceived social image (Sweeney & Soutar, 2001); Mean = 2.03; Cronbach α = .87; AVE = .76	
Shopping in a smart retail store would allow me to be a VIP customer	.75
Shopping in a smart retail store would give me a more acceptable image	.92
Shopping in a smart retail store would improve how people perceive me	.92
Shopping in a smart retail store would give me a good impression to others	.90
Mean	.87
Privacy concerns (Hong & Thong, 2013); Mean = 3.68; Cronbach α = .84; AVE = .78	
It bothers me if smart retail stores collect my information	.91
I am worried about the information these stores could get about me	.90
It bothers me to not control the information smart retail stores can get	.84
Mean	.88
Innovativeness (Steenkamp & Gielens, 2003); Mean = 3.44; Cronbach α = .71; AVE = .69	
If I hear about a new technology, I like to try it	.77
I am usually the first one to use a new technology in my entourage	.72
I feel able to use a new technology by myself	.71
Mean	.73
High-wellbeing personality (Hock, 1962; Attié & Meyer-Waarden, 2018); Mean = 3.72; Cronbach α = .69; AVE = .59	
I am able to generate lots of enthusiasm	.82
I am often in a good mood	.75
I feel positive most of the time	.70
Mean	.75

Variable (adapted scale); scales reliability indicators	Factor loadings
Low-wellbeing personality (Hock, 1962; Attié & Meyer-Waarden, 2018); Mean = 2.65; Cronbach α = .69; AVE = .58	
I am often in a bad mood	.71
I often erase myself in front of others	.77
I often feel sad	.76
Mean	.74
High-empowered personality (Hock, 1962; Attié & Meyer-Waarden, 2018); Mean = 3.47; Cronbach α = .68; AVE = .56	
I have a strong mental	.70
I know how to control myself and my emotions	.76
I know how to deal with stressful situations	.72
Mean	.71
Low-empowered personality (Hock, 1962; Attié & Meyer-Waarden, 2018); Mean = 3.01; Cronbach α = .71; AVE = .63	
I often feel nervous	.70
I am rather anxious	.82
I stress easily	.86
Mean	.79

Table 29: Scales reliability indicators (*Article 5; acceptance of smart connected stores*)

Then, discriminant validity is assessed with the square root of AVE for each variable (see Table 30). The boldfaced numbers along the diagonal represent the square root of AVE, and the elements off diagonal are the inter-scale correlations.

Constructs	Intention to visit	Intention to buy	Privacy concerns	Perceived social image	Perceived well-being
Intention to visit	.88				
Intention to buy	.65***	.84			
Privacy concerns	-.26***	-.22**	.87		
Perceived social image	.10***	.44**	-.15**	.87	
Perceived well-being	.22***	.55**	-.02ns	.48**	.85

*** mean p -value < .001; ** p -value < .01; * p -value < .1; ns = non-significant.

Table 30: Correlations of the latent variables (*Article 5; acceptance of smart connected stores*)

The square root of AVE for each construct is higher than the correlations on corresponding row and column and above .50, showing good discriminant validity (Fornell & Larcker, 1981).

2.4.2.4. Results

2.4.2.4.1. Results of the structural model testing the main effects

The data is analyzed with structural equation modelling using SPSS Amos 21. Amos can be used since the multivariate normality analysis is acceptable (see Appendix 6A), the sample size is greater than 200 observations and we want to confirm theoretically assumed relationships. The estimated direct path coefficients are reported in Table 31.

Dependent variable	Independent variable	Hypothesis	β coefficient	t-value
Intention to buy R ² =.70	Intention to visit	H1	.66***	11.03***
	Privacy concerns	H2	-.26***	-4.69***
Intention to visit R ² =.66	Perceived well-being	H4	.22***	3.45***
	Perceived social image	H6	.10*	1.89**
	Privacy concerns	H3	-.02ns	-.32ns
Perceived well-being R ² =.52	Perceived social image	H5	.48***	10.88***

*** indicates p -value < .001; ** p -value < .01; * p -value < .1; ns = non-significant

Table 31: Results of the estimated direct path coefficients (*Article 5; acceptance of smart connected stores*)

Figure 28 sums up these results with the model fit indicators.

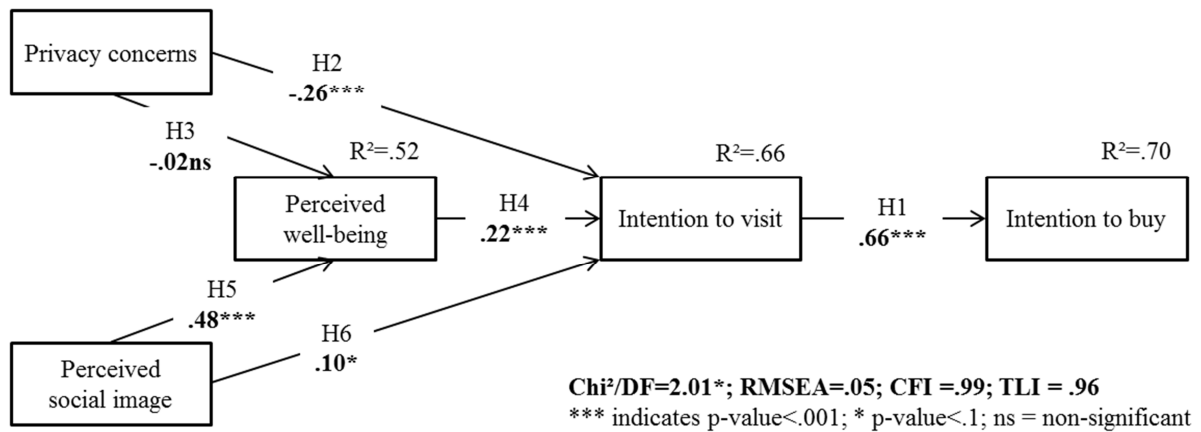


Figure 28: Conceptual model and model fit indicators (*Article 5; acceptance of smart connected stores*)

Table 31 and Figure 28 show that the model explains 70% of the variance in the intention to buy, 66% in the intention to visit, and 52% in perceived well-being. The model fit is acceptable with $\chi^2/DF < 5$ (Byrne, 2006), $RMSEA < .08$ (Browne & Cudeck, 1993), $CFI > .80$ (Bentler, 1990), $TLI > .80$ (Bentler & Bonett, 1980).

The intention to visit smart retail stores positively influences the intention to buy ($\beta = .66$; $p < .05$); H1 is supported. Privacy concerns about the data collection negatively influence the intention to visit ($\beta = -.26$; $p < .05$) but do not influence significantly perceived well-being ($\beta = -.02$; $p < .70$); H2 is supported and H3 is not supported. Then, perceived well-being positively influences the intention to visit smart retail stores ($\beta = .22$; $p < .05$); H4 is supported. Besides, perceived social image positively influences perceived well-being and the intention to visit smart retail stores (respectively $\beta = .48$; $p < .05$; $\beta = .10$; $p < .10$); H5 and H6 are supported.

2.4.2.4.2. *Results of the structural model testing the moderating effects*

To test the moderating effects, Process model 1 from Hayes is used (see Table 32). Process is a regression path analysis modelling tool widely used in research for estimating moderation effects (Hayes et al., 2017).

H7 Moderator: Innovativeness			
H1 Intention to visit -> Intention to buy	H2 Privacy concerns -> Intention to visit	H4 Well-being -> Intention to visit	H6 Perceived social image -> Intention to visit
positive effect $\Delta R^2=1\%$	non-significant	non-significant	non-significant
H8 Moderator: Well-being personality			
H1 Intention to visit -> Intention to buy	H2 Privacy concerns -> Intention to visit	H4 Well-being -> Intention to visit	H6 Perceived social image -> Intention to visit
negative effect $\Delta R^2=1\%$	negative effect $\Delta R^2=1\%$	negative effect $\Delta R^2=1\%$	negative effect $\Delta R^2=1\%$
H9 Moderator: Empowered personality			
H1 Intention to visit -> Intention to buy	H2 Privacy concerns -> Intention to visit	H4 Well-being -> Intention to visit	H6 Perceived social image -> Intention to visit
positive effect $\Delta R^2=1\%$	positive effect $\Delta R^2=1\%$	non-significant	non-significant

Table 32: Main moderating effects (*Article 5; acceptance of smart connected stores*)

Table 32 (see Appendix 6B for details) shows that consumer innovativeness positively moderates the influence of the intention to visit smart retail stores on the intention to buy ($\Delta R^2 = 1\%$); H7 is partly supported. Then, a well-being personality negatively moderates the influences of the intention to visit smart retail stores on the intention to buy ($\Delta R^2 = 1\%$), of privacy concerns on the intention to visit smart retail stores ($\Delta R^2 = 1\%$), of perceived well-being on the intention to visit ($\Delta R^2 = 1\%$), and of perceived social image on the intention to visit ($\Delta R^2 = 1\%$); H8 is partly supported. Furthermore, an empowered personality positively moderates the influences of the intention to visit smart retail stores on the intention to buy

($\Delta R^2 = 1\%$) and of privacy concerns on the intention to visit ($\Delta R^2 = 3\%$); H9 is partly supported.

2.4.2.4.3. Control variable

In line with the literature, gender is tested as a control variable (see Table 33) to provide a stronger test of the hypotheses (Gefen & Straub, 1997; Venkatesh & Morris, 2000). Also, as the video stages a man choosing clothes, we want to make sure this doesn't affect the results with potential gender identification.

	R²	ΔR^2	F (p-value)
Without control variables	.70		
With gender	.69	0%	21.06 (.001)

Table 33: Control variable indicators (*Article 5; acceptance of smart connected stores*)

Table 33 shows that gender has no significant influence on the acceptance of smart retail stores.

2.4.2.5. Discussion

This paper advances earlier research on technology acceptance with a broader perspective (Atkins & Kim, 2012) by developing an integrative framework of the acceptance of smart retail stores. Our results confirm the role of various factors in determining consumer acceptance and resistance of smart retail stores. The roles of privacy concerns, perceived social image, perceived well-being, and of personalities are highlighted in the context of smart connected shopping. Results show a statistically significant and consistent theoretical model (Wheaton et al., 1977), which can be applied in future research about IoT and smart retail stores contexts.

More specifically, our results show that the intention to visit smart retail stores positively influences the intention to buy as in existing research (Foroudi et al., 2018; Laroche & Brisoux, 1989; Laroche & Sadokierski, 1994; Teng & Laroche, 2007). Consumers are more willing to buy when they initially have positive beliefs and attitudes toward smart retail stores (Foroudi et al., 2018; Ngo & O'Cass, 2013). As well in line with existing research, perceived well-being positively influences the intention to visit smart retail stores, confirming that value

is not only perceived from utilitarian benefits but also from the relational, well-being and experience associated benefits (Bruner & Kumar, 2005; Çelik & Yılmaz, 2011; Chiu et al., 2014; Curran & Meuter, 2007; Dabholkar & Bagozzi, 2002; Hirschman & Holbrook, 1982; Johar & Awalluddin, 2011; Kim & Forsythe, 2008; Koufaris 2002; Kulviwat et al., 2007; Novak et al., 2000; Sherman et al., 2001; Van der Heijden, 2004). Research showed that shopping is fun to do (Arnold & Reynolds, 2003; Wakefield & Baker, 1998). However, this result might depend on the context (Wang, 2017). For example, a supermarket self-checkout is more a utilitarian service where consumers prefer to not spend too much time, and therefore do not need or expect fun from this consuming experience (Wang, 2017). On the opposite, well-being has a stronger impact in hedonic service contexts (Van der Heijden, 2004). Our context of study was a non-utilitarian, rather hedonistic smart retail stores selling clothes, which can explain this result. In line with the literature, it appears that consumers envisage positive emotions from this shopping experience, positively influencing attitudes towards this kind of stores (Andreasen et al., 2012; Curran & Meuter, 2007; Dabholkar & Bagozzi, 2002; Davis & Pechmann, 2013; Koufaris, 2002; Perugini & Bagozzi, 2001; Weijters et al., 2007). Furthermore, the literature about new technology adoption still contributes little to the knowledge about well-being influence (Hall & Khan, 2002). Shopping can fulfil fundamental human needs like autonomy, competence, and social interactions (Tauber, 1972). Satisfying these needs thus plays an important role in improving perceived well-being (e.g., Deci & Ryan, 2002). We furthermore confirm that social image improves perceived well-being through social satisfaction (Hoffman, 2012; Kuisma et al., 2007; Naci & Ioannidis, 2015). Perceived social image positively influences the intention to visit smart retail stores as well, in line with existing research (Bandura, 1986; Compeau & Higgins, 1995; Foroudi et al., 2018; Guzzo et al., 2016; Venkatesh & Davis, 2000).

These findings also provide insights about customer resistance to smart retail stores. Little research has investigated privacy concerns in the context of smart retail stores (Fox & Royne, 2018; Verhoef et al., 2017). In line with the literature, privacy concerns about data collection are the main barriers to the acceptance of the IoT: trust and transparency are thus necessary for acceptance (Hoffman et al., 1999; Portes et al., 2016). However, privacy concerns do not influence significantly perceived well-being, in contrast to theory (Shin, 2010; Van der Heijden, 2004; Wünderlich et al., 2015): there seems to be no increase of stress if the benefits of personalization are higher than the loss of privacy (Xu et al., 2011). An increasing number of users give up privacy concerns simply by aiming to live a personalized experience

and to belong to a desired social group (Turow et al., 2008). However, privacy concerns differ according to people's perceptions and values, and might differ with contexts (Donaldson & Dunfee, 1994; Malhotra et al., 2004). Indeed, there could be a difference between sensitive and more general data: the data sharing should be clear with the volume of data collected and analyzed, in order to define the acceptable perimeter of privacy sharing. The influence of privacy concerns might also be non-significant when users are uncertain about how companies collect, use, and manage consumer data (Sheehan & Hoy, 1999).

Concerning the different types of consumers, the following finding is pointed out: the more consumers are characterized by a high level of innovativeness, the more smart retail stores are accepted. This confirms previous research: consumers react differently to innovations due to their degree of innovativeness (Rogers, 1983) and innovative consumers are more likely to accept smart technologies and environments (Agarwal & Karahanna, 2000), including smart retail stores. Similarly, high-empowered consumers are more attracted to smart retail stores, favouring the acceptance process. As for innovators, high-empowered consumers have an ability to convince peers through word-of-mouth actions if performing a specific action (e.g., visiting a smart retail store) improves their social image and ascertain a specific social status within their social group (Hellström, 2004). Low-empowered consumers are also easily accepting smart retail stores, which might be counter-intuitive. An explanation might be that low empowered consumers are usually shy people who do not want to be noticed by others, and as smart retail stores decrease social interactions, that might be a reason why they are also likely to visit smart retail stores. Furthermore, another counter-intuitive result is that low-wellbeing consumers easily accept smart retail stores, feeling less privacy concerns than hypothesized. An explanation might be that these consumers look for improving productivity and social interactions, and smart retail stores might be a way to gain time and share with other people a smart personalized experience, thus decreasing privacy concerns (e.g., Xu et al., 2011). Furthermore, they might enjoy receiving notifications and personalized feedback, which lowers their sense of loneliness and sadness increasing well-being. For high-wellbeing consumers, hedonism is the main goal in life (e.g., Mill, 1998). Therefore, since they are very socially orientated, they might dislike the idea to replace employees by automatized smart objects, which decreases social interactions. Another hypothesis of the low acceptance of these consumers is that the smart retail store in the video could seem more utilitarian (e.g., gain of time, access to real-time information) than hedonic to them and this type of consumers might be more attracted to hedonic innovations, and not just regular innovations.

2.4.2.6. Managerial contributions

The evolution of the IoT brings some implications for retail managers. If consumers' expectations are satisfied, they are more likely to adopt these new technologies and become buyers (Applebaum, 1998; Levinas, 1997). Even if prices and utility are important, consumer experience, well-being and social benefits appear to become more and more significant for consumers, adding meaningful value to differentiate stores from competitors (Kim et al., 2017; Novak et al., 2000). Consumers can be loyal to brands but connectivity pushes them to be loyal to several brands at once through notification push for example. It is important for companies to differentiate them through quality because dissatisfaction can push consumers to other brands while satisfaction should keep them loyal. Yet, loyalty programs in grocery retailers are more efficient with customers who live closer to the store, because they earn those benefits faster (Meyer-Waarden & Benavent, 2009). If Internet technologies are initially mainly used by younger generations, they appear now widely accepted by all generations (Foroudi et al., 2018). But, the efficacy of loyalty programs also depend on social categories, generations, and loyalty to the brand (Meyer-Waarden & Benavent, 2003).

Understanding the needs of connected consumers implies to change the way companies used to define their strategies (Verhoef et al., 2009). The IoT aims at answering to different needs according to consumers, retailers and managers. The advantages for customers are the ability to identify where the clothes are located in the store with their smartphone, to choose another size or color inside the fitting room via the smart mirror, and receive real-time offers by notifications on their smartphone. For retailers, the advantages are to receive notifications from the fitting room when the customer asks for another size or color, identify where the clothes are located thanks to a RFID tag, and support each customer visiting the store. Finally, for managers, the advantages are to get real time alerts about the stock to manage it (analytics), to define and send personalized notifications, to analyze the customer journey in store to better define the merchandising strategy, and to analyze customers' profiles (i.e., man, woman, age, etc.). Eric Bachié, Percall's Director of IoT business comments that companies "have invested significantly in putting together a realistic taster of what shoppers can look forward to in tomorrow's connected world and it is all achievable today." These solutions based on the principles of the nudge economy (i.e., detecting hesitant buyers to incentivize them to complete a purchase) offer the opportunity to create a more efficient point of sale leading to greater productivity and profits. The nudge economy allows tracking and analyzing

footfall of customers, sending on-the-spot offers to phones of logged-in customers and collecting feedback from no-buy shoppers. Retail technologies then monitor and analyze customer traffic and behavior in order to send immediate and interactive offers to customers. Figure 29 summarizes the global view of smart retail stores market according to consumers, companies, and IoT solutions.

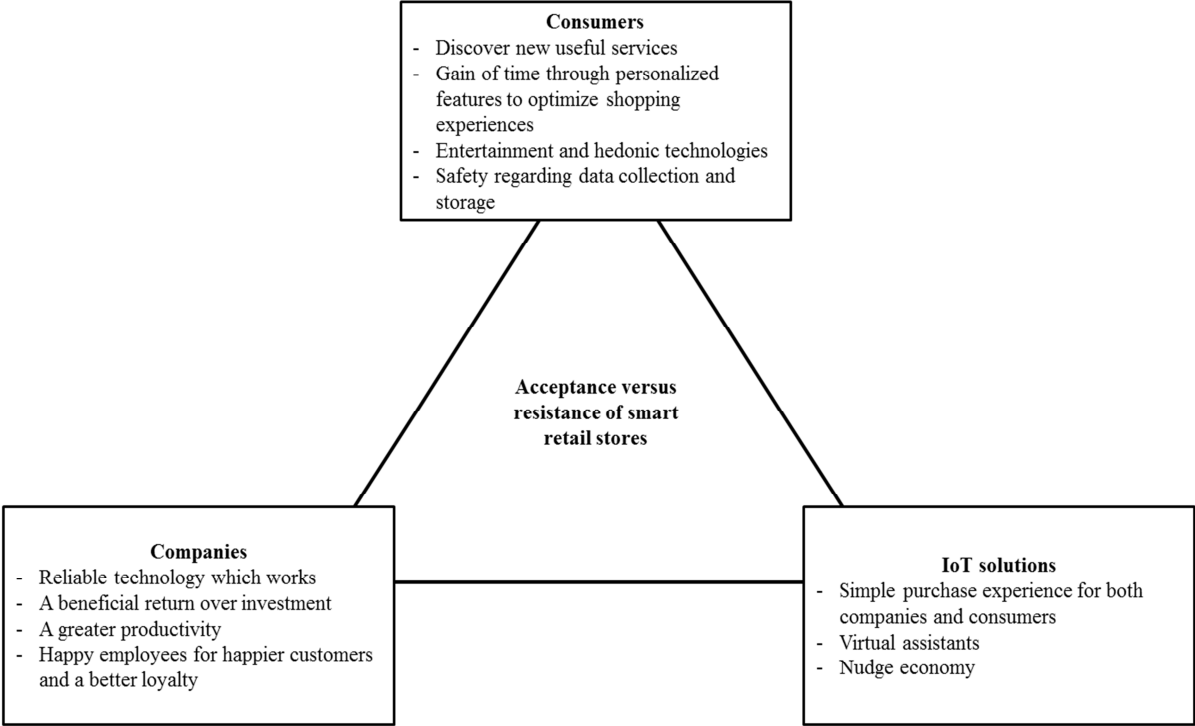


Figure 29: Global view of the smart retail store market

A huge amount of big data can also be obtained and analyzed through analytical tools (Lee & Lee, 2015). This can be very useful for management and marketing decisions to create an individual value-added service experience for consumers through real-time event feedback (Lee & Lee, 2015; Remondes & Afonso, 2018). However, there is still a need to overcome the security hurdle that slows down the development and extension of IoT opportunities (Lee & Lee, 2015; Suo et al., 2012). Confidentiality, privacy, and trust between users, companies and smart devices, still need to be better regulated and more transparent (Lee & Lee, 2015). Furthermore, ethical issues can arise, due to the ubiquity, omnipresence, and unpredictable characteristics of the IoT (Van der Hoven, 2013). Yet, even if in this study, it appears that privacy concerns do not increase stress when consumers believe that the personalization and social benefits are higher than the loss of privacy (Xu et al., 2011). Data security must be a central topic in product/service development, data policies and communication, to increase

trust towards the brand (Bhattacharjee, 2000; Hengstler et al., 2016; Shieh et al., 2013). Thus, retailers should be transparent concerning the data collection (Portes et al., 2016) and usage management in order to reassure consumers and increase their willingness to visit and buy in smart retail stores. Moreover, Kaul (2005) shows that stores with modern equipment, good and clean facilities, and ease in transactions improve satisfaction and intentions.

Furthermore, strategies should focus more on consumers, their characteristics, needs, beliefs, interests and values, rather than on the average purchase. The connected consumer wants services with a 360° vision: consultation of the availability of each product and its location in the store, real-time information, a fast checkout, etc. Indeed, the new consumer is becoming more and more connected. Personality traits, such as innovativeness, have more impact on consumer behaviors toward technologies (Rogers, 1983). Therefore, it is highly recommended to define types of consumers attracted to smart retail stores. Consumers react differently to innovations due to their degree of innovativeness (Rogers, 1983). The more consumers are characterized by a high level of innovativeness, the more smart environments are accepted (Agarwal & Karahanna, 2000). Regarding the high versus low empowered and well-being personality, each personality can find appealing aspects in accepting IoT environments. High-empowered consumers are naturally more attracted to smart environments (Attíe & Meyer-Warden, 2018), favouring the acceptance process of smart retail stores. As for innovators, high-empowered consumers have an ability to convince peers through word-of-mouth actions if performing a specific action (e.g., visiting a smart retail store) improves their social image and ascertain a specific social status within their social group (Hellström, 2004). Advices from friends and close relatives also have a higher impact than those from experts and people tend to overestimate their friends' abilities (Bertrandias & Vernet, 2012). Regarding low-empowered users, the policies of data privacy and use should be clear and transparent. Low-empowered consumers could also easily accept smart retail stores as technology decreases social interactions, which are not favoured by these personalities (Attíe & Meyer-Warden, 2018). However, people with a high well-being personality might be more attracted by real social interactions and they might dislike the idea to replace employees by automatized smart objects, which decreases social interactions. Therefore, keeping employees in stores might be a way to increase smart retail stores acceptance, or else, favouring hedonic innovations (e.g., environments adapting to consumers' moods, interactive robots). Indeed, these consumers look for senses of excitement, and hedonism is their main goal in life (e.g., Mill, 1998). Therefore, increasing smart distractions and entertainment through relationships and

immersion with personalized service features should improve smart retail stores acceptance (Seligman, 2011). Concerning low well-being consumers, personalized feedback and encouragements should please them, as they are rather anxious and lonesome. Therefore, visiting a smart retail store could be a way to gain time and share with other people a smart personalized experience, decreasing privacy concerns (e.g., Xu et al., 2011). Marketing strategies should thus focus on reinforcing innovative brand status, image and recognition, in order to fit with these consumers' values. To sum up, Table 34 shows the main characteristics of consumers and their needs.

Personality	Main traits	Main needs
Innovative	Attracted to new technologies, curious, open-minded, intuitive, technophile	Discover new technologies and services, and get an easy and fast access to connectivity through Wi-Fi networks
High-empowered	Self-controlled, energetic, strong-minded, with a strong leadership, proud	Improve a social status through a social action (i.e., visiting a smart retail store)
Low-empowered	Diplomatic, vigilant, hesitant, suspicious	Be reassured regarding safety of technologies, and have fewer social interactions with people
High-wellbeing	Positive, dynamic, talkative, inconstant, irrational, thoughtless	Be entertained through smart devices like virtual headsets, virtual games, smart screens, robots, and have more social interactions with people or personalized features
Low-wellbeing	Thinker, listener, careful, rational, easily tensed, anxious, distressed	Increase productivity with a gain of time (i.e., less queue at the check-out, information about each products, location in the store), and have personalized features

Table 34: The main traits of personality of consumers and needs

2.4.2.7. Limits and further research directions

Despite several contributions to the literature, this research has limitations and leaves some questions unanswered. The sample principally comes from the Y and Z generations, making it hard to generalize these results to all generations. Indeed, if Internet technologies are initially mainly used by younger generations, they appear now widely accepted by all generations (Foroudi et al., 2018) and studies also show that these generations are less anxious about technology, have less need for interaction with employees, and are thus more inclined to accept smart environments (Dabholkar, 1996; Meuter et al., 2003). Further research should therefore use more respondents from all generations. In addition, it would be interesting to use real-time data and field experiments to study consumers' perceptions and behaviours before, during and after their outlet visit, and do longitudinal investigations about loyalty and other benefits (i.e., consumer well-being, purchase behaviour). Besides, this study was done in a rather hedonic smart retail store context (e.g., clothing store), limiting thus generalizability. Thus, it would be interesting to replicate this study in a utilitarian retail context (e.g., grocery store like AmazonGO). Future research should also compare results between smart versus non-smart stores to see if there are differences between the type of stores and consumer targets, as well as with other types of smart environments like smart cities since the number of smart cities has rapidly increased, improving quality of life and raising various issues as well (Granier & Kudo, 2016; N'Goala, 2016).

Another concern of companies and consumers is about the reduction of people in stores. Machines can replace employees and thus decrease human interactions between buyers and retailers. This also implies that the IoT creates new kinds of jobs in engineering, network, computer science, or that sellers will have to become image consultants, for example, to provide an added value in a near future.

Moreover, in the literature, fear is often studied as a persuasive strategy used to influence consumer attitudes and behaviors (Fishbein & Ajzen, 1975). For example, fear has been used to address public health issues such as smoking prevention, driving under the influence of alcohol, or poor eating habits (e.g., Freimuth & Mettger, 1990). Another problem with the IoT is that a connected environment necessarily implies the presence of electromagnetic pollution. In 2011, the International Agency for Research on Cancer judged the radiation from connected objects to be potentially carcinogenic. According to other specialists, these objects

emit very low-frequency radiation that is then harmless to humans. In reality, it is still too early to analyze the real effects of prolonged and cumulative exposure to these small radiations. It will take more time to obtain significant results regarding these health controversies.

Summary of contributions

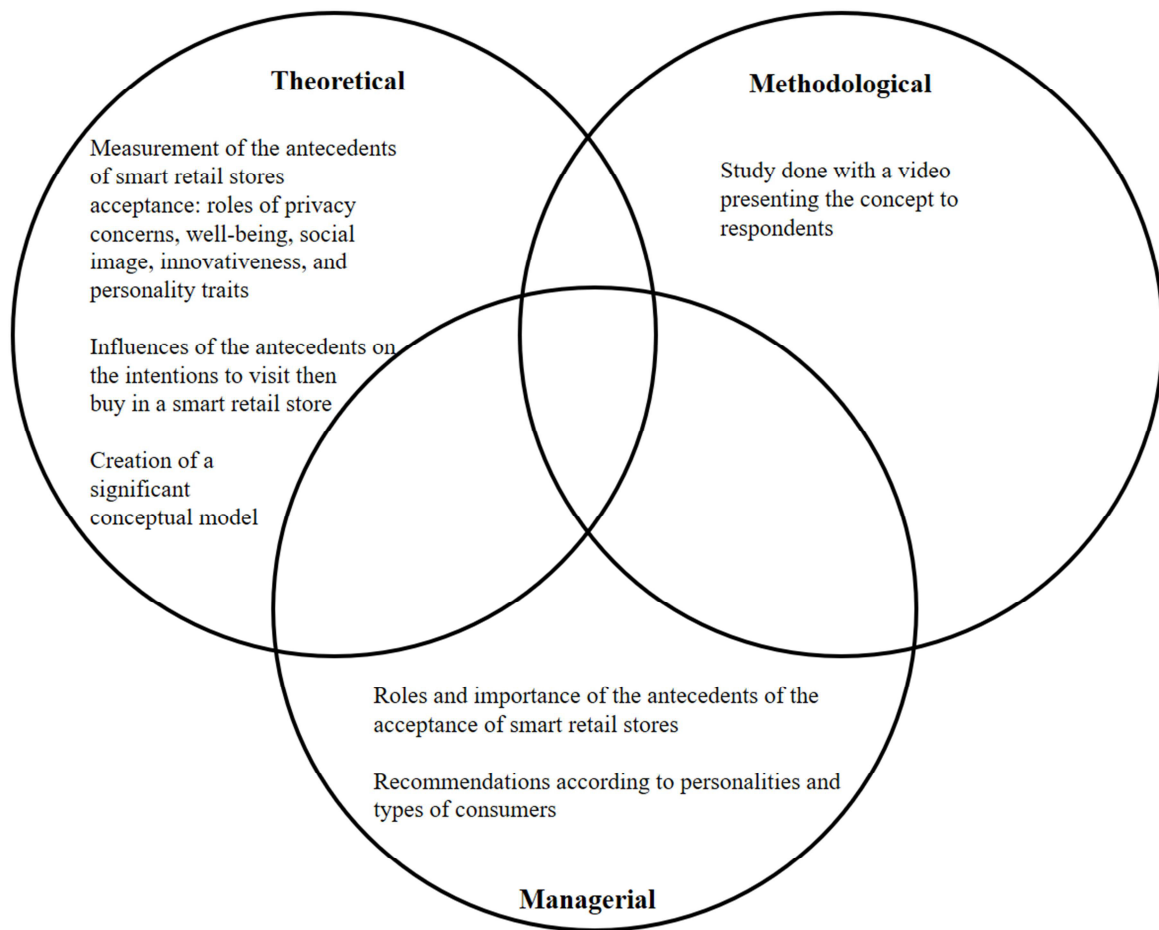


Figure 30: Summary of contributions (*Article 5; acceptance of smart connected stores*)

If we sum up our main contributions, Figure 30 shows that there are three main contributions:

- (1) Theoretical contributions: we highlight the roles of antecedents of smart stores acceptance: TAM's main variables, perceived well-being, perceived social influence, privacy concerns, and types of personalities;
- (2) Methodological contributions: we show our respondents a video to present the concept of smart retail stores, in order to increase the understanding of our study;
- (3) Managerial contributions: we show the importance of the antecedents, and how to recognize types of consumers and potential targets in order to improve the acceptance process.

Conclusion to Chapter 2

The IoT and smart technologies represent a growing market, as it is a highly relevant marketing tool as well. It is therefore essential that companies understand the acceptance and use (Verhoef et al., 2017). The findings of this chapter 2 are in line with existing theory and should enhance the understanding of the acceptance as well as the usage process of the IoT and smart technologies. Users are likely to use the IoT and smart technologies when it offers well-being and health benefits, usefulness and data/health safety, creating development opportunities for entertainment, health, and sport trackers or environments. On the other side, privacy concerns negatively influence the IoT and components acceptance. Thus, data security must be a central topic in both development and communication, and companies must be clear with users concerning data protection and policies. According to our different studies, there are common results to generalize about the acceptance and adoption of the IoT and smart technologies. Table 35 summarizes the antecedents of acceptance, by order of importance with 1 = high importance.

Antecedents of adoption	Physical objects	Mobile apps	Smart environments	
	Smart objects	Sleep apps	Smart homes	Smart stores
Qualitative studies	Well-being (1) Privacy concerns (1) Social value (2) PU (3) PEU (4) <i>Moderator: Innovativeness</i>	Well-being (1) Privacy concerns (1) PU (2) PEU (3) <i>Moderator: Quantified-self</i>	Well-being (1) Privacy concerns (1) Utility value (2) <i>Moderator: Well-being personality</i>	Well-being (1) Privacy concerns (1) Utility value (2) Social image (3) <i>Moderator: Empowered personality</i>
Quantitative studies	<u>Acceptance:</u> PU (1) PEU (2) Well-being (3) Social image (4) <u>Loyalty of use:</u> Well-being (1) PU (2) PEU (2) Social image (3) <i>Moderators: Privacy concerns,</i>	<u>Before use:</u> PU (1) Quantified-self (2) PEU (3) Well-being (4) <u>After use:</u> PU (1) PEU (2) Quantified-self (3) Well-being (4) <i>Moderators: Privacy concerns, well-being</i>	Well-being (1) Utility value (2) Social image (3) Privacy concerns (4) <i>Moderators: Quantified-self, innovativeness well-being personality, empowered personality</i>	Privacy concerns (1) Well-being (2) Social image (3) <i>Moderators: innovativeness, well-being personality, empowered personality</i> <i>Non-significant: Utility value, quantified-self</i>

Antecedents of adoption	Physical objects	Mobile apps	Smart environments	
	Smart objects	Sleep apps	Smart homes	Smart stores
	<i>innovativeness</i>	<i>personality,</i> <i>empowered</i> <i>personality</i> <u><i>Non-significant:</i></u> <i>Social image,</i> <i>innovativeness</i>		

PU stands for perceived usefulness; PEU for perceived ease of use.

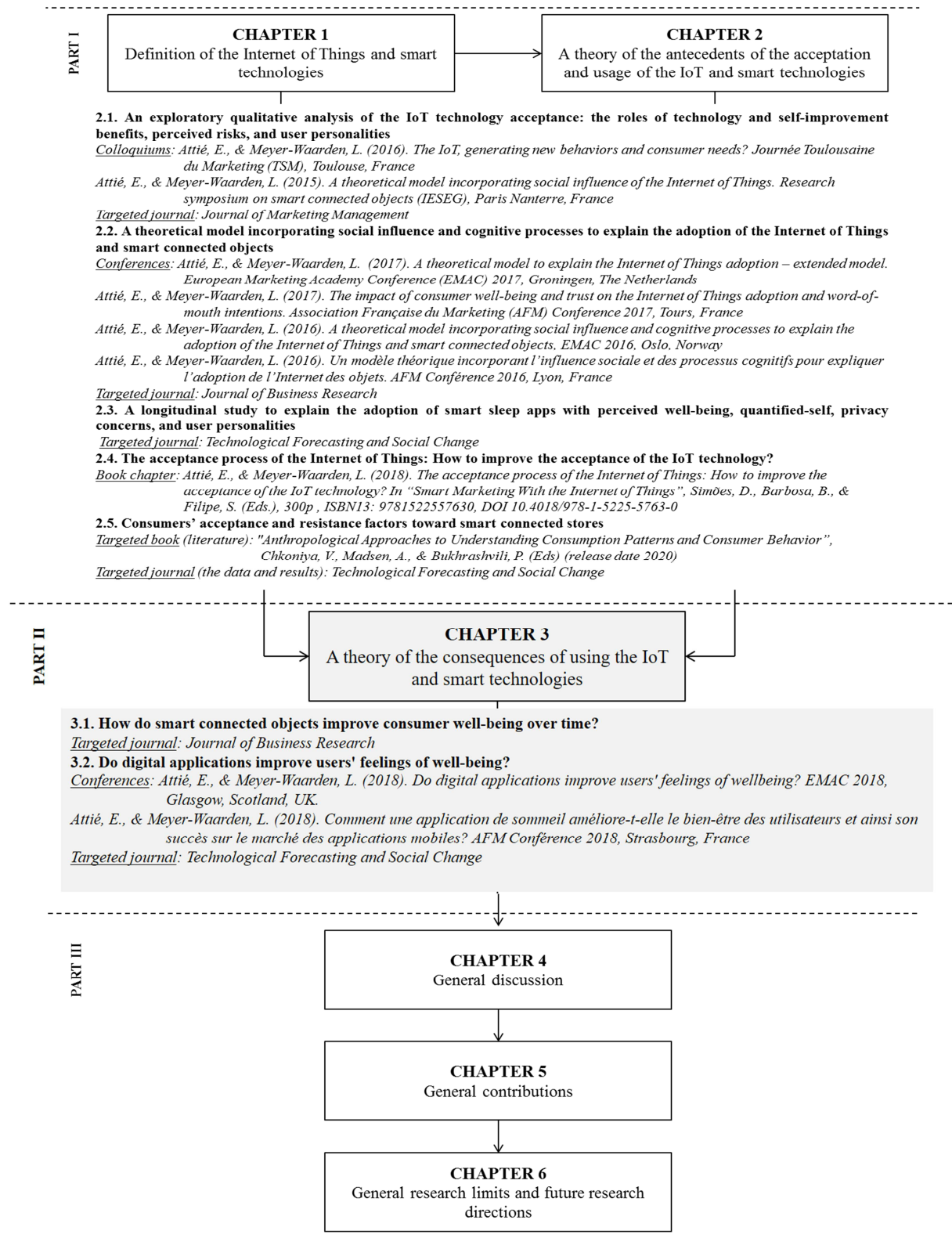
Table 35: Summary of the antecedents of the IoT and smart technologies acceptance

Table 35 shows that our qualitative studies allow to highlight different antecedents according to the IoT context. For SCO, our quantitative study confirms these results but the order of importance changes, with PU and PEU which are more important than perceived well-being, then perceived social image is more important than use; however, after adoption and use, perceived well-being becomes the most important antecedent.

For sleep apps, perceived well-being, privacy concerns, perceived social image, PU and PEU seem to be important antecedents of acceptance as well. This time, the order of importance differs with our quantitative study and remains the same before and after use with PU and PEU first, followed by perceived well-being.

Finally, with smart environments, the same antecedents (i.e., perceived well-being, privacy concerns, utility value) are highlighted, with perceived social image added when it is a social action like with smart stores. More specifically, with smart homes, well-being is the most important antecedents, whereas with smart stores, privacy concerns are the most important antecedents of acceptance. This summary shows the importance to combine mixed methods with qualitative and quantitative research, and different contexts of technologies to better understand the acceptance and usage of smart technologies.

PART II



Another main goal of this thesis is to test the consequences of the IoT and smart technologies namely their influence on perceived well-being. To do this, we study two contexts of study already mentioned in Part I of this thesis: SCO and sleep apps. Therefore, we build conceptual models explaining the influences of IoT and smart technologies on perceived well-being. We define perceived well-being, in the consumer context, as a desired state of objective and subjective well-being related to a better health, social activity, happiness, contentment, fulfilment, involvement, and quality of life, leading to positive judgements and emotions toward choices of consumption and long-term positive consequences. Results show that the TAM main variables (i.e., PU, PEU, IU, real use) have a direct influence on perceived well-being, as well as perceived social image, if the technology is visible to other people (i.e., with SCO). With SCO, experience of use decreases privacy concerns through better abilities and feelings of control over the technology, which in turn improves perceived well-being. However, a sleep app decreases feelings of well-being, increasing the perceived stress linked to low usefulness and high privacy concerns. Therefore, the consequences of the IoT and smart technologies depend on the technology itself (i.e., SCO or sleep app), and on personality traits (i.e., high versus low well-being personalities). The chapter 3 of this thesis thus presents two articles about the way the IoT and smart technologies influence perceived well-being:

1. Influence of smart objects on well-being: How do smart connected objects improve consumer well-being over time? (*Article 6 (Part 2 of Article 2); section 3.1.*)
2. Influence of smart apps on well-being: Do digital applications improve users' feelings of well-being? (*Article 7 (Part 2 of Article 3); section 3.2.*)

CHAPTER 3: A THEORY OF THE CONSEQUENCES OF USING THE IOT AND SMART TECHNOLOGIES

Introduction to Chapter 3

Another main goal of this thesis is to better understand the consequences of using the IoT and smart technologies on perceived well-being. This chapter 3 highlights relevant antecedents of well-being with two contexts of study (i.e., SCO and a sleep app). Here are the different studies presented in this chapter:

1. How do smart connected objects improve consumer well-being over time? (*Attié, E., & Meyer-Waarden, L., intended to be combined with Article 2*) is a study that shows that the TAM main variables (PU, PEU, real use) and perceived social image influence perceived well-being. With experience of use, perceived social image and innovativeness both increase whereas privacy concerns decrease, improving perceived well-being.
2. Do digital applications improve users' feelings of well-being? (*Attié, E., & Meyer-Waarden, L., paper presented at Rencontres AFM/Syntec 2019 Paris, EMAC 2018 Glasgow, AFM 2018 Strasbourg; intended to be combined with Article 3*) is a paper showing that the main TAM variables (PU, PEU, IU and real use) influence perceived well-being. Experience of use decreases these feelings of well-being, due to a decrease of usefulness and an increase of privacy concerns. However, the adoption is influenced by the role of personalities.

As mentioned in our literature review in the general introduction, research has pointed out conceptual issues about perceived well-being. Table 36 is a brief summary of well-being antecedents and gaps from the literature that we target in this thesis.

Reference	Antecedents of well-being	Future research directions
Beaudry & Pinsonneault, 2010	<ul style="list-style-type: none"> - Opportunities influence: benefits maximizing, benefits satisficing - Threats influence: disturbance handling, self-preservation 	<ul style="list-style-type: none"> - Find significant samples from France
Van Ittersum et al., 2013	<ul style="list-style-type: none"> - Utility value 	<ul style="list-style-type: none"> - Examine other types of behaviors and technologies (i.e., health trackers, nutritive apps, etc.)

Reference	Antecedents of well-being	Future research directions
Chiu et al., 2014	- Technology design	- Do longitudinal studies
Fang et al., 2014	- Accessibility, reducing task complexity, elimination of intermediation	- Construct suitable well-being measures and test it on a larger sample size and in other countries
Higgsa & Dulewicz, 2014	- Personality and emotional factors	- Test other antecedents - Find a wider sample
Anderson & Ostrom, 2015	- Consumer-centric, experiential and co-creation strategies, control, knowledge	- Study personal attributes like personalities and emotions
Sanzo-Perez et al., 2015	- Perceived abilities	- Find potential moderators of the links between the variables
Ahmadpour et al., 2016	- A lack of control, knowledge, and privacy	- Reproduce this study with a significant sample
Hsieh et al., 2016	- Service performance, contributions to others' well-being, happiness, satisfaction	- Focus on specific technologies
Teh et al., 2017	- Feeling powerful	- Focus on technologies targeted to young generations
Gonzalez et al., 2017	- Identification, utility, hedonism, social values, frequency of apps use	- Study other contexts and antecedents - Do longitudinal studies
Munzel et al., 2018	- Size and intimacy of social networks through social capital	- Study other operationalizations of well-being (Paim, 1995) and privacy concerns (Jiang et al., 2013)
Wunderlich et al., 2019	- Motivation, household demographic, electricity-consumption, perceived privacy risk, innovation	- Do longitudinal studies before/after use to study the evolution of the relationships between the variables
Bhat et al., 2019	- Dimensions: social, hedonic, personal development and well-being aspects	- Develop and test a well-being scale - Use empirical and mixed research approaches

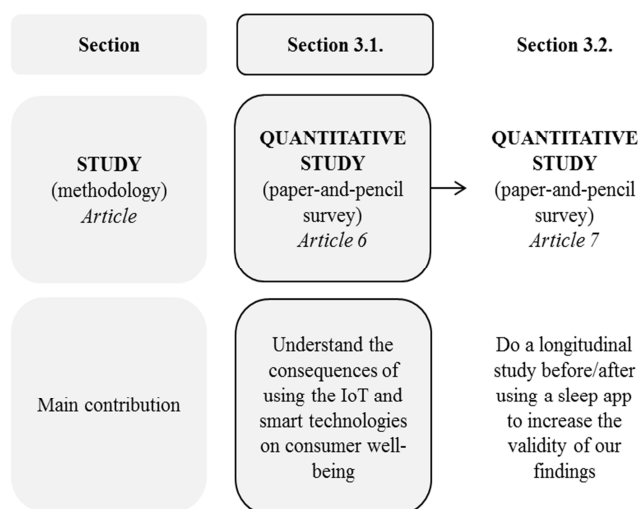
Table 36: The well-being antecedents and gaps developed in this thesis

Table 36 shows that the literature points out research gaps to be addressed, like finding significant samples (Ahmadpour et al., 2016; Beaudry & Pinsonneault, 2010; Fang et al., 2014; Higgsa & Dulewicz, 2014), conducting longitudinal studies (Chiu et al., 2014; Gonzalez et al., 2017; Wunderlich et al., 2019), focusing on specific technologies (Hsieh et al., 2016; Teh et al., 2017; Van Ittersum et al., 2013), using empirical and mixed research approaches (Bhat et al., 2019), constructing suitable well-being scales (Fang et al., 2014; Luca & Suggs, 2013), or testing significant antecedents (Anderson & Ostrom, 2015; Gonzalez et al., 2017; Higgsa & Dulewicz, 2014; Sanzo-Perez et al., 2015). Therefore, regarding the literature and the limits of our samples, we study the influence of perceived abilities with quantified-self (Ahmadpour et al., 2016; Sanzo-Perez et al., 2015; Teh et al., 2017), satisfaction (Hsieh et al., 2016), technology trust (Sannes & Kim, 2018), social values (Gonzalez et al., 2017), privacy concerns (Ahmadpour et al., 2016), gender (Joshani et al., 2012), personality and emotional factors (Higgsa & Dulewicz, 2014), and the main TAM's variables such as perceived ease of use (Fang et al., 2014), perceived usefulness (Gonzalez et al., 2017; Van Ittersum et al., 2013), and real use (Gonzalez et al., 2017).

By studying these antecedents and by choosing a specific methodology described in each study, we aim to respond to the following research gaps pointed out in the literature, and to contribute in the following ways. Firstly, we want to study specific variables and find moderators that are relevant according to the literature (Anderson & Ostrom, 2015). Secondly, we use empirical and mixed research approaches, and we focus on specific technologies (Kyriakopoulos & Moorman, 2004). Thirdly, we develop and test a well-being scale statistically valid in the IoT and smart technologies context (Luca & Suggs, 2013). Fourthly, we conduct a longitudinal study before/after use to study the evolution of the relationships (Berry, 1995).

Thus, the first article deals with the adoption of SCO over three years of use. The second article is about the consequences of using a sleep app, before and after using it for one week, to test if the consumers' expectations meet the outcomes after use.

In the next section 3.1., we present a quantitative study about the consequences of SCO on well-being, according to stages of adoption (early adopters, the early majority, the late majority of users).



3.1. Influence of smart objects on well-being: How do smart connected objects improve consumer well-being over time? (Article 6)

Abstract

Consumer well-being is increasingly becoming a discussion topic in the marketing literature (Arora et al., 2017). In this study, we aim to explain the consequences of the Internet of Things (IoT) and smart connected objects (SCO), namely their influence on perceived well-being. Therefore, we study in a longitudinal study over three years the direct influences of the Technology Acceptance Model (TAM)'s main variables, such as real use, perceived usefulness, perceived ease of use, and perceived social image on perceived well-being. We add privacy concerns and innovativeness as moderators to this conceptual model. Also, we study differences in perceptions according to adoption stages: early adopters at year 1, early majority of users at year 2, and the late majority of users at year 3 (Rogers, 1962). The data comes from 595 random respondents surveyed over three years. Structural equation modelling shows that the main TAM variables (e.g., perceived usefulness, perceived ease of use, and real use) are still relevant in the SCO context. Real use is the most important antecedent during all the adoption stages, whereas perceived usefulness and ease of use are less important. The influence of perceived usefulness is only significant with the early majority of users. Moreover, perceived social image gives more positive feelings to users with time. We also show that the experience of use decreases privacy concerns whereas it increases innovativeness and the perceived well-being associated with SCO.

Figure 31 sums up our main objectives and methodology for this study:

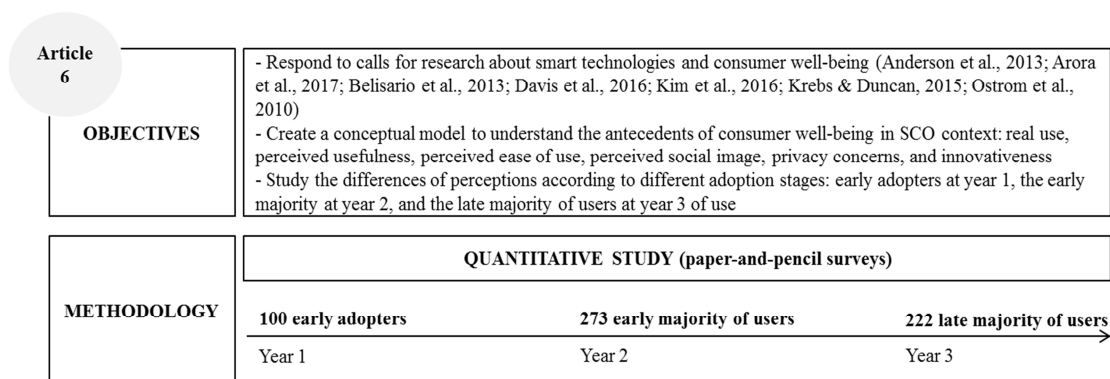


Figure 31: Main objectives and methodology (*Article 6; influence of SCO on well-being*)

3.1.1. Introduction

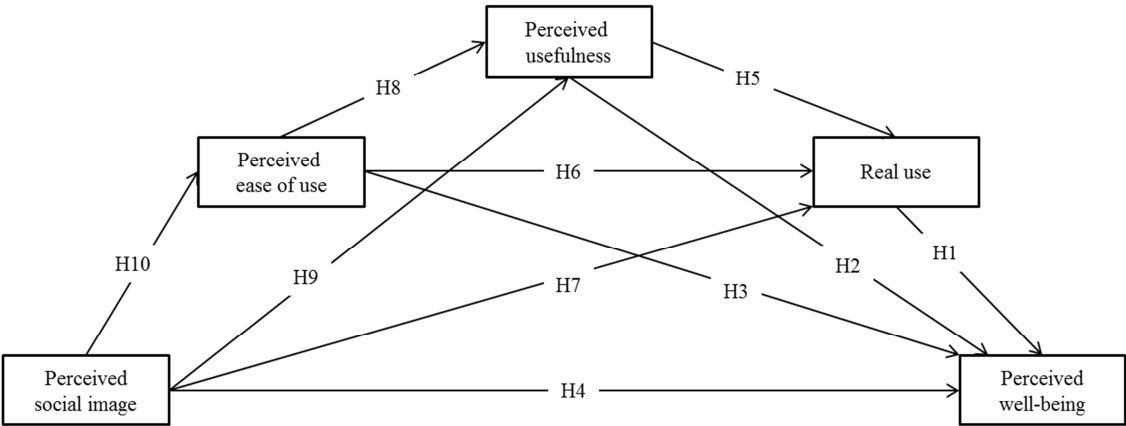
Smart connected objects (SCO) can connect to smartphones through wireless networks (e.g., smart watches, smart clothes, smart home robots, etc.). SCO are defined as active, digital, networked, controlling things (Poslad, 2009) with artificial intelligence to adapt their features to environmental indicators. SCO should improve consumer well-being (Atzori et al., 2010; Porter & Heppelmann, 2014; Xia et al, 2012). Perceived well-being is defined as a subjective state of fullness resulting from judgments, emotions and aspirations about the perception of a current situation, compared to a past or future of the person or entourage (Ayadi et al., 2019). Little is known in marketing about the variation of perceived well-being over time, although it is an important determinant of choices (Mogilner et al., 2012). Besides, the concept of well-being is increasingly attracting attention from researchers and managers (Arora et al., 2017). However, Etkin (2016) then Gonzalez and colleagues (2017) have shown that using smart technologies might negatively influence well-being over the long term. Moreover, users can change their use and beliefs about technology over time (Ashraf et al., 2014; Gilly et al., 2012; Rogers, 2003). Since the results may be contrary and there is a lack of research on this topic, there are calls for research into the influence of using SCO on perceived well-being (Arora et al., 2017; Kim et al., 2016; Krebs & Duncan, 2015).

Therefore, this study builds on previous research concerning the relevance of the main variables of the TAM when studying SCO (i.e., perceived usefulness, perceived ease of use, real use). On the other hand, as the TAM is often considered insufficient to explain other and new antecedents of technology adoption (Benbasat & Barki, 2007; Chuttur, 2009), we enhance it by introducing a social variable with the perceived social image, perceived risks with privacy concerns, and personality traits with innovativeness. These are under-investigated in the marketing and management literature regarding SCO. Moreover, the innovation diffusion literature mostly focuses on pre-adoption perceptions (Anderson & Ortinau, 1988; Huh & Kim, 2008). As research shows that it is important to consider different adoption stages, our conceptual model is empirically tested with three sets of data collected over three years (2015-2018) and from different stages of SCO adoption (e.g., early adopters, early majority of users, late majority of users; Rogers, 1962).

This article is organized as follows: first, the theory and conceptual framework are described in section 3.1.2.; then, the methodology is explained in section 3.1.3.; afterwards, the results are presented in section 3.1.4., followed by a discussion in section 3.1.5., and by theoretical and managerial contributions in section 3.1.6; finally, we conclude with the limits and future research directions in section 3.1.7.

3.1.2. Literature review

The TAM (Davis, 1989) is highly used and recommended by the literature to explain technology adoption (King & He, 2006; Venkatesh et al., 2003). It has strong psychometric properties that can be used in different contexts (King & He, 2006; Lederer et al., 2000; Legris et al., 2003). As the directions of the influences are not clear between adoption and perceived well-being (Steptoe, 2012), we choose the TAM main variables (perceived usefulness, perceived ease of use, real use) as antecedents of perceived well-being. Our conceptual model is represented in Figure 32. This model shows that perceived well-being should be influenced by other variables as well, such as perceived social image (PSI), perceived risks —with privacy concerns—, and personality traits —with innovativeness—.



Moderators: privacy concerns (H11); innovativeness (H12)

Figure 32: Conceptual model (Article 6; influence of SCO on well-being)

Researchers recognize the importance of studying perceived well-being (Su et al., 2014). Perceived well-being is linked to physical health (Rozanski & Kubzansky, 2005), mental health (Su et al., 2014), quality of life and hedonism (Ayadi et al., 2017; Diener & Chan, 2011), and consumer choices (Gilovich et al., 2015). Consumers’ subjective well-being is a long-term satisfaction (Zhong & Mitchell, 2012). Perceived well-being is the degree to which

consumers perceive experiences in positive ways, through cognitive judgments and affective reactions, without objective facts (Diener, 1984). Smart technologies should enhance consumer well-being by improving quality of life (Atzori et al., 2010; Etzioni, 1999; Harkin et al., 2016; Kluger & DeNisi, 1996; Porter & Heppelmann, 2014; Xia et al., 2012). Indeed, a better well-being can come from the ease of use of self-tracking, self-knowledge, and of self-management with SCO (Ahern et al., 2006; Gibbons et al., 2011; Gustafson et al., 2002). However, other research has shown the opposite results. Etkin (2016) shows that using smart health devices decreases well-being over the long term, due to the consequences of technology dependence and stress. Gonzalez and colleagues (2017) have demonstrated similar results with mobile apps. Since the results in the literature are mitigated by the impact of SCO on feelings of well-being, and since there is a lack of research on this topic, further studies about the impact of smart technologies on well-being are highly recommended (Anderson et al., 2013; Arora et al., 2017; Kim et al., 2016; Krebs & Duncan, 2015). Therefore, we hypothesize:

H1: The real use of SCO has a positive influence on well-being that decreases over time

Moreover, better self-knowledge and self-management improves the perceived usefulness (PU) (Katz et al., 1974). PU is the degree to which people believe that using a technology will help them to improve their performance (Davis, 1989). There is a link between utility value and hedonism, thanks to the experience of use (Aurier et al., 2004). Therefore, SCO should fit with daily routines, subsequently improving well-being (e.g., Dhar & Wertenbrach, 2000; Spangenberg et al., 2003; Strahilevitz & Myers, 1998; Van der Heijden, 2004). Other research has also demonstrated that the more people find a technology useful, the more they perceive well-being because it gives them a rational reason to keep on using this technology (Gonzalez et al., 2017; Van Ittersum et al., 2013). Thus, we hypothesize:

H2: PU has a positive influence on well-being that increases over time

Furthermore, easy-to-use technologies increase the perceived abilities of people, positively enhancing their well-being (Sanzo-Perez et al., 2015). Perceived ease of use (PEU) is the degree to which the use of a technology is perceived as easy and free of effort (Davis, 1989). It has been shown that the accessibility of a technology and low task complexity improve well-being (Fang et al., 2014). Easy to use technologies seem more reassuring to users, improving pleasure of usage (Gu et al., 2010). If the technology seems too hard to use, people

can feel a lack of control and knowledge, which decreases their perceived well-being (Ahmadpour et al., 2015). Therefore, we hypothesize:

H3: PEU has a positive influence on well-being that increases over time

Using SCO can also give a positive social image to users, which improves positive feelings toward the technology (Kuisma et al., 2007; Rogers, 1983). Perceived social image (PSI) is the degree to which the use of a product enhances social status within a social group (Moore & Benbasat, 1991). Research has demonstrated that social values have a positive influence on well-being because users feel it is consistent with their own-self to use this technology and that it improves their daily life (Aurier et al., 2004; Gonzalez et al., 2017; Seligman, 2003). Thus, we hypothesize:

H4: PSI has a positive influence on well-being that increases over time

Moreover, PU and PEU are strong determinants of technology usage (Davis, 1989; Calantone et al., 2006; Taylor & Todd, 1995). People have a more positive attitude toward a new technology when it is associated with utility benefits, such as PU or PEU, and tend to use it more often (King & He, 2006; Venkatesh & Davis, 2000). Therefore, we hypothesize:

H5: PU has a positive influence on real use that increases over time

H6: PEU has a positive influence on real use that increases over time

Then, the role of social value could also be relevant in explaining technology usage (Bagozzi, 2007; Venkatesh & Davis, 2000). The Social Cognitive Theory shows that technology adoption is affected by PSI (Bandura, 1986; Compeau & Higgins, 1995). Indeed, using an innovation, such as SCO, can give a positive social image that then improves acceptance and use (Kuisma et al., 2007; Rogers, 1983). Therefore, a new technology seen as conforming socially is more likely to be used, and it becomes a social action (Hellström, 2004). Thus, we hypothesize:

H7: PSI has a positive influence on real use that increases over time

In addition, the TAM (Davis, 1989) has shown that PEU is a direct determinant of PU. Indeed, easy-to-use technologies seem more accessible and useful than technologies, which

seem hard to learn and use (Davis et al., 1989; Gefen & Straub, 2000; Pavlou, 2003; Taylor & Todd, 1995; Venkatesh, 1999; Venkatesh & Morris, 2000). Therefore, we hypothesize:

H8: PEU has a positive influence on PU that increases over time

Nevertheless, performing a specific behavior can be consistent with group norms to achieve group membership, social support, and group identification through social image (Kiesler & Kiesler, 1969; Pfeffer, 1981). Improving a social image can be seen as useful for people eager to improve their social image and status within their social group (e.g., Hellström, 2004). Thus, we hypothesize:

H9: PSI has a positive influence on PU that increases over time

Furthermore, the closer the technology's image seems to be to users' self-image, the more they should find the technology easy to use because the technology then looks more familiar to them (Cowart et al., 2008; Sirgy, 1985). Therefore, we hypothesize:

H10: PSI has a positive influence on PEU that increases over time

Research has also shown that situational factors and normative constraints moderate the links between the variables (Morwitz et al., 1993; Sheppard et al., 1988). The way SCO track and collect personal data can be seen as intrusive, increasing privacy concerns (Awad & Krishnan, 2006; Hong & Thong, 2013; Phelps et al., 2001). Privacy concerns represent the degree to which users are concerned about the flow of their information (Phelps et al., 2000). When users perceive risks regarding the way their data is used by SCO, they tend to develop feelings of stress that subsequently decrease positive feelings toward the technology (Van der Heijden, 2004; Wünderlich et al., 2015). These feelings of stress ultimately lead to the rejection of the technology (Lynch & Ariely, 2000). Therefore, we hypothesize:

H11: The effects hypothesized in H5, H6, and H8 are weaker (stronger) when consumers have higher (lower) privacy concerns about SCO

Finally, according to the Innovation Diffusion Theory, people may react differently to new products due to personality traits, like innovativeness (Rogers, 1983). People who are more innovative have more positive beliefs about SCO than less innovative people (Agarwal & Karahanna, 2000; Eastlick & Lotz, 1999; Goswami & Chandra, 2013; Reynolds & Ruiz De

Maya, 2013). In addition, personality and emotional factors positively influence the way people perceive feelings of well-being (Higgs & Dulewicz, 2014). Thus, we hypothesize:

H12: The effects hypothesized in H5, H6 and H8 are weaker (stronger) when consumers have a lower (higher) innovativeness

3.1.3. Methodology

3.1.3.1. Description of the scales

The variables are measured with validated scales from prior research that we adapt to the context of our study (e.g., ‘In general, I feel well with my SCO’). To measure real use, we select the scale from Chau (1996); for perceived usefulness and perceived ease of use, we choose Davis’ (1989) scale; for perceived well-being, we adapt a scale from Munzel and colleagues (2018), Brief and Aldag (1977), Howie and colleagues (1998), and Diener and colleagues (1985); for social image, we use a scale developed by Sweeney and Soutar (2001); for privacy concerns, we use the scale from Hong and Thong (2013); and, for innovativeness, we use the scale from Steenkamp and Gielens (2003). Items are measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

3.1.3.2. Administration of the survey and sample

The quantitative study was conducted from January 2015 to March 2018 with paper-and-pencil surveys with French students from Toulouse School of Management (University of Toulouse Capitole 1). The samples comprised: 100 users using SCO (i.e., smart watch, smart tablet, smart tv, etc.) at year 1, 273 users using SCO at year 2, and 222 users using SCO at year 3. There is no extreme value on one variable or multivariate data that could influence the results, and the sample sizes (N1 = 100; N2 = 273; N3 = 222) have a satisfying representativeness (Hinkin, 1995). Table 37 presents their gender characteristics.

Stage	Characteristic	N	Percentage
Early adopters	Gender Man	53	53%
	Woman	47	47%
Early majority	Gender Man	162	59%
	Woman	111	41%

Stage	Characteristic	N	Percentage
Late majority	Gender Man	143	64%
	Woman	79	36%

Table 37: Descriptive characteristics of the samples (*Article 6; influence of SCO on well-being*)

According to the proportions of men and women, we can consider gender as a control variable (Gefen & Straub, 1997; Venkatesh & Morris, 2000) to test if gender influences the results.

3.1.3.3. Reliability and validity of the items and scales

To validate the scales and keep or discard items, we use the factor loadings and means by variable which show how much a factor explains a variable (i.e., factor loadings > .70; Anderson & Gerbing, 1988), the Cronbach α to show the reliability of the psychometric test (i.e., Cronbach α > .70; Nunnally, 1978), and the average variance extracted (AVE) for construct reliability (i.e., AVE scores > .50; Fornell & Larcker, 1981). Scales show a good reliability and validity in the context of SCO and the variables meet the necessary conditions of normality for regressions. The final items, scales, and reliability indicators are detailed in Table 38.

Variable (scales reliability indicators)	Factor loadings		
	Year 1	Year 2	Year 3
Use (Year 1: Cronbach α = .80, AVE = .63, Mean = 4.06; Year 2: Cronbach α = .84, AVE = .69, Mean = 3.86; Year 3: Cronbach α = .85, AVE = .69, Mean = 3.97)			
I use a lot my SCO in my daily life	.81	.89	.89
I use my SCO in my daily life if possible	.63	.79	.79
I frequently use my SCO in my daily life	.80	.89	.89
I use my SCO in my daily life when needed	.89	.73	.73
Mean	.78	.82	.82
Intention to use (Year 1: Cronbach α = .80, AVE = .83, Mean = 3.69; Year 2: Cronbach α = .81, AVE = .84, Mean = 2.07; Year 3: Cronbach α = .81, AVE = .84, Mean = 3.45)			
Looking at its benefits, I intend to use SCO in my daily life	.91	.92	.92
If I have access to my SCO, I intend to use it more often	.92	.93	.92
Since I have access to my SCO, I use it	.91	.92	.91
Mean	.91	.92	.92

Variable (scales reliability indicators)	Factor loadings		
	Year 1	Year 2	Year 3
Perceived usefulness (Year 1: Cronbach $\alpha = .73$, AVE = .65, Mean = 3.39; Year 2: Cronbach $\alpha = .87$, AVE = .72, Mean = 3.78, Mean = 3.78; Year 3: Cronbach $\alpha = .86$, AVE = .71, Mean = 3.89)			
My SCO is a good assistant during my daily life	.74	.86	.86
My SCO helps me to do my tasks faster and saving time	.72	.84	.83
My SCO makes my daily life easier	.88	.88	.88
My SCO is very useful	.87	.82	.80
	Mean	.80	.85
		.84	
Perceived ease of use (Year 1: Cronbach $\alpha = .83$, AVE = .66, Mean = 4.20; Year 2: Cronbach $\alpha = .77$, AVE = .59, Mean = 4.12; Year 3: Cronbach $\alpha = .77$, AVE = .59, Mean = 4.21)			
I find it easy to use my SCO	.81	.83	.83
Using my SCO is clear and understandable	.89	.85	.86
I feel competent to use my SCO	.85	.67	.65
I feel that my SCO is adapted to my daily life	.68	.71	.71
	Mean	.81	.77
		.76	
Perceived well-being (Year 1: Cronbach $\alpha = .77$, AVE = .63, Mean = 2.81; Year 2: Cronbach $\alpha = .73$, AVE = .57, Mean = 3.09; Year 3: Cronbach $\alpha = .75$, AVE = .58, Mean = 3.12)			
I like using my SCO as it is a fun distraction	.63	.51	.52
My SCO allows me to improve my health	.74	.76	.77
My SCO improves my quality of life	.84	.83	.83
In general, I feel better since I started using my SCO	.88	.87	.88
	Mean	.77	.74
		.75	
Perceived social image (Year 1: Cronbach $\alpha = .97$, AVE = .91, Mean = 2.52; Year 2: Cronbach $\alpha = .90$, AVE = .79, Mean = 2.41; Year 3: Cronbach $\alpha = .90$, AVE = .77, Mean = 2.39)			
My SCO gives me a more acceptable image	.94	.89	.88
My SCO improves how people perceive me	.97	.89	.87
My SCO gives a good impression of me to others	.97	.89	.88
My SCO gives me a better social approval	.95	.87	.87
	Mean	.96	.88
		.87	

Variable (scales reliability indicators)	Factor loadings			
	Year 1	Year 2	Year 3	
Privacy concerns (Year 1: Cronbach α = .94, AVE = .85, Mean = 4.02; Year 2: Cronbach α = .90, AVE = .78, Mean = 3.55; Year 3: Cronbach α = .90, AVE = .77, Mean = 3.42)				
I fear my SCO collects my information	.89	.88	.88	
It bothers me when my SCO collects my information	.96	.91	.89	
I fear SCO use my data for purposes I do not know about	.92	.89	.88	
It bothers me to not control the information my SCO gets from me	.91	.85	.84	
	Mean	.92	.88	.87
Innovativeness (Year 1: Cronbach α = .70, AVE = .63, Mean = 3.14; Year 2: Cronbach α = .75, AVE = .67, Mean = 3.26; Year 3: Cronbach α = .76, AVE = .67, Mean = 3.38)				
If I hear about a new technology, I like to try it	.83	.82	.84	
I am the first one in my group to use a new technology	.84	.84	.83	
I feel able to use a new technology by myself	.71	.79	.80	
	Mean	.79	.82	.82

Table 38: Scales reliability indicators (*Article 6; influence of SCO on well-being*)

Then, we assess discriminant validity with the square root of AVE for each variable. The bold numbers along the diagonal represent the square root of AVE, and the elements off diagonal represent the inter-scale correlations (Table 39).

Early adopters						
Constructs	Use	IU	PU	PEU	WB	PSI
Real use	.89					
IU	.39*	.89				
PU	.62**	.56**	.85			
PEU	.48**	.43**	.59**	.87		
WB	.18ns	.49**	.38**	.32**	.87	
PSI	.30**	.56**	.54**	.26**	.44**	.98

Early majority of users						
Constructs	Use	IU	PU	PEU	WB	PSI
Real use	.82					
IU	.06**	.92				
PU	.55**	.38**	.85			
PEU	.42**	.29**	.52**	.77		
WB	.39**	.58**	.52**	.33**	.75	
PSI	.21**	.42**	.40**	.09**	.55**	.89
Late majority of users						
Constructs	Use	IU	PU	PEU	WB	PSI
Real use	.82					
IU	.34**	.92				
PU	.51**	.34**	.84			
PEU	.39**	.25**	.53**	.77		
WB	.39**	.57**	.49**	.32**	.76	
PSI	.19**	.40**	.35**	.06ns	.57**	.88

*** indicates p -value < .001; ** p -value < .01; * p -value < .1; IU stands for intention to use, PU for perceived usefulness, PEU for perceived ease of use, WB for well-being, PSI for perceived social image.

Table 39: Correlations of the latent variables (*Article 6; influence of SCO on well-being*)

Table 39 shows that the square root of AVE for each construct is higher than the correlations on corresponding row and column and above .50, showing a good discriminant validity (Fornell & Larcker, 1981).

3.1.3.4. Differences of means

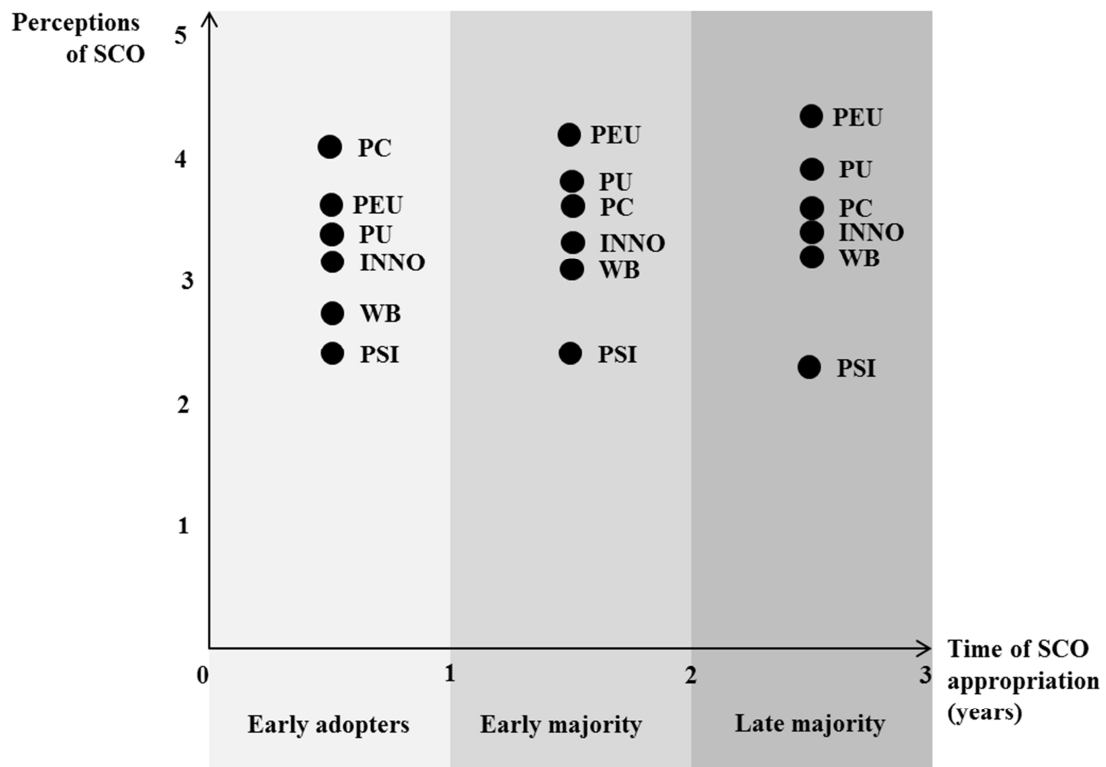
Table 40 presents the differences of means between the adoption stages. We use Levene's test to evaluate the equality of variance. It indicates that when p-values are above .05, the variances are not significantly different.

Construct	Mean			F (p-value)
	Early adopters	Early majority	Late majority	
Real use	4.06	3.86	3.97	5.64(.001)
Intention to use	3.69	2.07	3.45	1.47(.23)
Perceived usefulness	3.39	3.78	3.89	9.74(.00)
Perceived ease of use	4.20	4.12	4.21	8.37(.00)
Perceived well-being	2.81	3.09	3.12	50.23(.00)
Perceived social image	2.52	2.41	2.39	1.44(.23)
Privacy concerns	4.02	3.55	3.42	12.80(.00)
Innovativeness	3.14	3.26	3.38	39.92(.00)

Table 40: Differences of means (*Article 6; influence of SCO on well-being*)

Table 40 shows that there are significant differences between early adopters, the early majority and the late majority of users with real use, PU, PEU, perceived well-being, privacy concerns, and innovativeness. The differences are not significant in relation to intention to use and perceived social image. More specifically, with experience of use, real use decreases (M1 = 4.06; M2 = 3.86; M3 = 3.97), PU increases (M1 = 3.69; M2 = 3.78; M3 = 3.89), PEU increases (M1 = 3.39; M2 = 4.12; M3 = 4.21), perceived well-being increases (M1 = 2.81; M2 = 3.09; M3 = 3.12), privacy concerns decrease (M1 = 4.02; M2 = 3.55; M3 = 3.42), and innovativeness increases (M1 = 3.14; M2 = 3.26; M3 = 3.38).

Figure 33 shows the evolution of these perceptions according to the three stages of adoption (e.g., early adopters, early majority of users, late majority of users).



SCO stands for smart connected objects; PC for privacy concerns, PEU for perceived ease of use, PU for perceived usefulness, INNO for innovativeness, WB for well-being, PSI for perceived social image.

Figure 33: Perceptions of SCO according to the time of appropriation (*Article 6; influence of SCO on well-being*)

Figure 33 shows that the main evolution is with privacy concerns, which decrease over time of appropriation and use. In addition, the perceived well-being and innovativeness significantly increase with the early majority of users and late majority of users.

3.1.4. Results

3.1.4.1. Structural model testing and its main effects

The data is analyzed via structural equation modelling (SEM) with Amos 21 from SPSS. The estimated direct path coefficients are reported in Table 41. See Appendix 7A for the multivariate normality analysis.

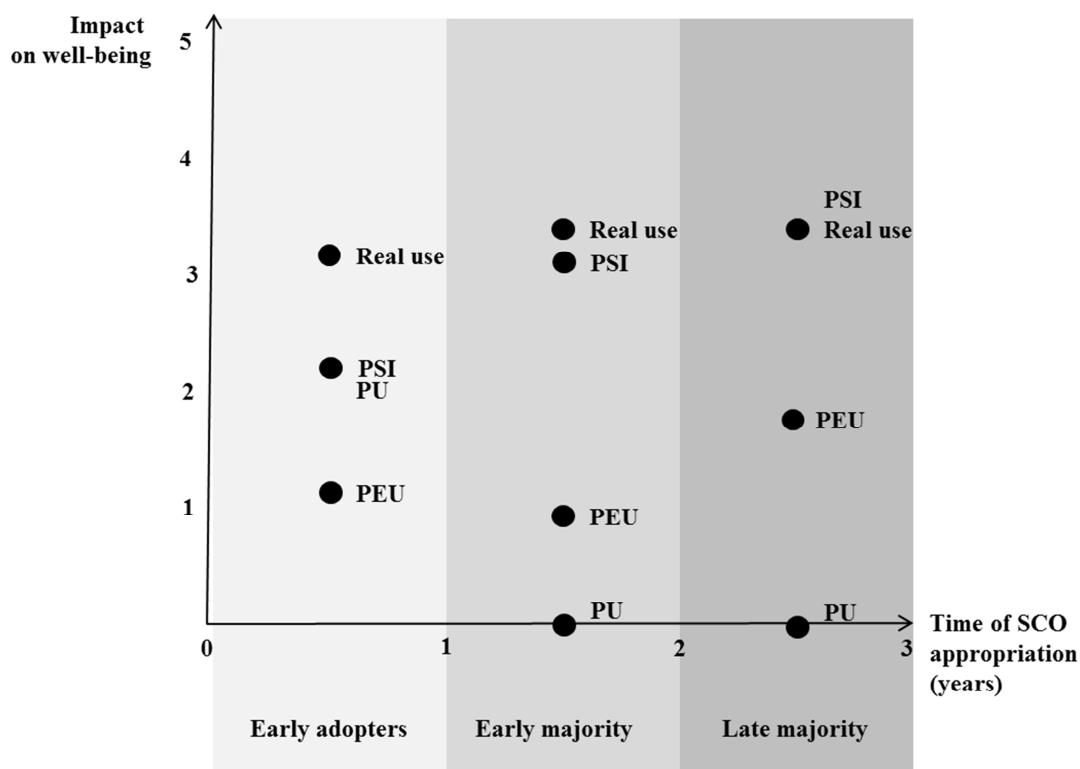
Dependent variable	Independent variable	Hypothesis	Early adopters (1)		Early majority (2)		Late majority (3)	
			β	t-value	β	t-value	β	t-value
WB R ² (1) =.54 R ² (2) =.72 R ² (3) =.68	Real use	H1	.31***	2.72 (.01)	.34***	6.91 (.00)	.34***	5.39 (.00)
	PU	H2	.02ns	.20 (.80)	.22***	4.00 (.00)	.11ns	1.54 (.12)
	PEU	H3	.11*	1.01 (.31)	.09*	1.80 (.07)	.17*	2.39 (.01)
	PSI	H4	.22*	1.94 (.05)	.31***	6.28 (.00)	.34***	6.00 (.00)
Real use R ² (1) =.43 R ² (2) =.51 R ² (3) =.46	PU	H5	.23*	2.07 (.04)	.14*	2.11 (.03)	-.06ns	-.62 (.53)
	PEU	H6	.19*	2.03 (.04)	.18*	3.02 (.00)	.33***	4.10 (.00)
	PSI	H7	.39***	4.29 (.00)	.31***	6.04 (.00)	.34***	4.80 (.00)
PU R ² (1) =.51 R ² (2) =.40 R ² (3) =.37	PEU	H8	.49***	6.69 (.00)	.48***	10.32 (.00)	.50***	9.19 (.00)
	PSI	H9	.41***	5.55 (.00)	.36***	7.51 (.00)	.20***	3.81 (.00)
PEU R ² (1) =.07 R ² (2) =.01 R ² (3) =.01	PSI	H10	.26***	2.67 (.01)	.09ns	1.55 (.12)	.03ns	.43 (.67)

*** indicates p -value < .001, ** p -value < .01, * p -value < .1; PU stands for perceived usefulness, PEU for perceived ease of use, WB for perceived well-being, PSI for perceived social image.

Table 41: Results of the estimated direct path coefficients (*Article 6; influence of SCO on well-being*)

Table 41 shows that the predictive power of perceived well-being is higher with the early majority and the late majority of users (respectively $R^2 = .72$; $R^2 = .68$). Moreover, real use has an increasing positive influence on perceived well-being with early adopters, the early majority and the late majority of users ($\beta = .31***$; $\beta = .34***$; $\beta = .34***$); H1 is supported. Then, PU has a positive influence on well-being only with the early majority of users ($\beta = .22***$) but not with early adopters and the late majority of users ($\beta = .02ns$; $\beta = .11ns$); H2 is supported with the early majority of users. PEU has an increasing positive influence on perceived well-being with early adopters, the early majority and the late majority of users ($\beta =$

.11*; $\beta = .09^*$; $\beta = .17^*$); H3 is supported. Then, PSI has an increasing positive influence on well-being with early adopters, the early majority and the late majority of users ($\beta = .22^*$; $\beta = .31^{***}$; $\beta = .34^{***}$); H4 is supported. Furthermore, PU has a positive influence on real use with early adopters and the early majority of users ($\beta = .23^*$; $\beta = .14^*$) and not with the late majority of users ($\beta = -.06ns$); H5 is supported with early adopters and the early majority of users. PEU has an increasing positive influence on real use with early adopters, the early majority and the late majority of users ($\beta = .19^*$; $\beta = .18^*$; $\beta = .33^{***}$); H6 is supported. PSI has a positive influence on real use with early adopters, the early majority and the late majority of users ($\beta = .39^{***}$; $\beta = .31^{***}$; $\beta = .34^{***}$); H7 is supported. Additionally, PEU has a positive influence on PU with early adopters, the early majority and the late majority of users ($\beta = .49^{***}$; $\beta = .48^{***}$; $\beta = .50^{***}$); H8 is supported. PSI has a positive influence on PU with early adopters, the early majority and the late majority of users ($\beta = .41^{***}$; $\beta = .36^{***}$; $\beta = .20^{***}$); H9 is supported. Finally, PSI has a positive influence on PEU with early adopters ($\beta = .26^{***}$), and not with the early majority and late majority of users ($\beta = .09ns$; $\beta = .03ns$); H10 is supported with early adopters. Figure 34 shows the variation of the impact of each variable on perceived well-being over time of appropriation and use.

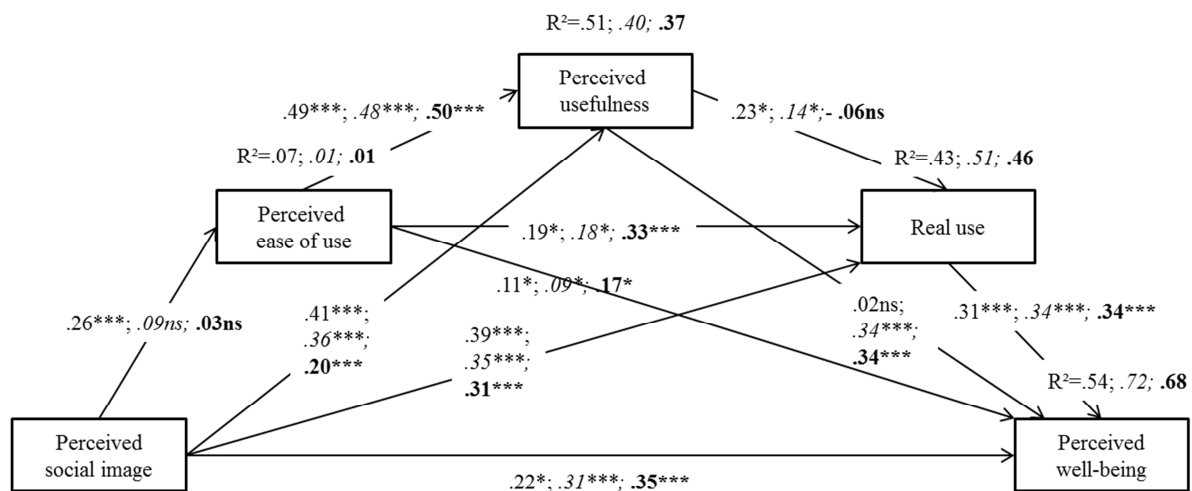


PEU stands for perceived ease of use, PU for perceived usefulness, PSI for perceived social image.

Figure 34: Impact of antecedents on well-being over the time of SCO appropriation (*Article 6; influence of SCO on well-being*)

Figure 34 shows that the influences of real use, PSI, PEU, and PU change over the time of appropriation of SCO. The influence of real use slightly increases over time, while the influence of PSI greatly increases over time. The variations in the influences of PEU and PU are neither linear nor constant. The influence of PEU slightly decreases for the early majority then increases for the late majority. Also, the influence of PU greatly increases for the early majority then greatly decreases for the late majority.

Moreover, the results of the factorial invariance analysis show that the model fit indicators are sufficient according to the guidelines ($\chi^2/DF < 5$ (Byrne, 2006); CFI coefficients $> .80$ (Bentler, 1990); TLI coefficients $> .80$ (Bentler & Bonett, 1980); RMSEA $< .08$ (Browne & Cudeck, 1993)). Thus, the model fit is acceptable for the whole adoption process, and it becomes better over time. Figure 35 shows a summary of the results with the theoretical model.



Early adopters: $\chi^2/DF=5.12^*$; RMSEA=.11; CFI=.89 TLI = .79
 Early majority: $\chi^2/DF=3.78^*$; RMSEA=.07; CFI=.96; TLI = .82
 Late majority: $\chi^2/DF=4.32^*$; RMSEA=.06; CFI=.98; TLI = .86
 *** indicates p-value<.001; ** p-value<.01; * p-value<.1; ns = non-significant

Figure 35: Conceptual model and model fit indicators (*Article 6; influence of SCO on well-being*)

3.1.4.2. Moderating effects

To test the effects of the moderators, Process model 1 from Hayes is used. Table 42 presents the main moderators' effects. Appendix 7B presents the details of the moderations.

H11 Moderator: Privacy concerns			
	H5: PU->Use	H6: PEU->Use	H8: PEU->PU
Early adopters	non-significant	negative effect $\Delta R^2=1\%$	negative effect $\Delta R^2=1\%$
Early majority	non-significant	non-significant	non-significant
Late majority	negative effect $\Delta R^2=1\%$	negative effect $\Delta R^2=1\%$	non-significant
H12 Moderator: Innovativeness			
	H5: PU->Use	H6: PEU->Use	H8: PEU->PU
Early adopters	positive effect $\Delta R^2=1\%$	positive effect $\Delta R^2=1\%$	non-significant
Early majority	positive effect $\Delta R^2=1\%$	positive effect $\Delta R^2=3\%$	positive effect $\Delta R^2=1\%$
Late majority	positive effect $\Delta R^2=1\%$	positive effect $\Delta R^2=1\%$	non-significant

Use stands for real use, PU for perceived usefulness, PEU for perceived ease of use.

Table 42: Main moderating effects (*Article 6, influence of SCO on well-being*)

Table 42 shows that with early adopters, privacy concerns negatively moderate the influence of PEU on real use and the influence of PEU on PU (for both $\Delta R^2 = 1\%$). With the early majority of users, privacy concerns do not moderate the links between the TAM variables. With the late majority of users, privacy concerns negatively moderate the influence of PU on real use and the influence of PEU on real use (for both $\Delta R^2 = 1\%$); H11 is partly supported.

Then, at year 1, innovativeness positively moderates the influence of PU on real use and the influence of PEU on real use (for both $\Delta R^2=1\%$). At year 2, innovativeness positively moderates the influence of PU on real use, the influence of PEU on real use and the influence of PEU on PU (respectively $\Delta R^2=1\%$; $\Delta R^2=3\%$; $\Delta R^2=1\%$). Finally, at year 3, innovativeness

positively moderates the influence of PU on real use and the influence of PEU on real use (for both $\Delta R^2=1\%$); H12 is partly supported.

Thus, studying privacy concerns and innovativeness as moderators of the relationships hypothesized regarding well-being adds some explanation to the model.

3.1.4.3. Control variables

In line with the literature, gender is tested as a control variable to provide a stronger test of the hypotheses (Gefen & Straub, 1997; Joshanloo et al., 2012; Venkatesh & Morris, 2000). Table 43 presents the test of this control variable.

	R ²	ΔR^2	F (p-value)
Early adopters			
Without control variables	.54		
With gender	.49	1%	6.21 (.001)
Early majority of users			
Without control variables	.72		
With gender	.67	1%	43.46 (.001)
Late majority of users			
Without control variables	.68		
With gender	.61	1%	21.09 (.001)

Table 43: Control variable indicators (*Article 6, influence of SCO on well-being*)

Table 43 shows that there is a difference between women and men for the three different stages of adoption, and the R² value decreases when gender is added to the model. However, this variation is very low ($\Delta R^2 = 1\%$).

3.1.5. Discussion

One of our main goals is to understand the consequences of SCO on perceived well-being. Our model shows a good fit according to the literature standards, and improves through the adoption stages. This suggests that experience of use positively changes consumer perceptions, following the disruptive innovation theory (Reinhardt & Gurtner, 2004).

This article follows plentiful previous research saying that TAM's main variables are relevant when studying technology use (Adams et al., 1992; Bagozzi et al., 2000; Bruner & Kumar, 2005; Chau, 1996; Davis, 1989; Davis et al., 1989; Davis et al., 1992; Hu et al., 1999; Jang & Noh, 2011; Kim et al., 2009; Mathieson, 1991; Muk & Chung, 2005; Pikkarainen et al., 2004; Ramayah et al., 2002; Taylor & Todd, 1995; Venkatesh & Davis, 1996; Wu & Wang, 2005). Another theoretical goal is to study the relevance of real use, PEU, PU, and PSI as direct predictors of perceived well-being, and of privacy concerns and innovativeness as moderators. The differences between the adoption stages confirm the literature showing that new technology adoption is a temporal sequence of stages (Huh & Kim, 2008).

After analyzing the data, we find that the influence of real SCO use on perceived well-being is positive, significant, and slightly increases over time of use, confirming one side of the literature (Atzori et al., 2010; Etzioni, 1999; Harkin et al., 2016; Kluger & DeNisi, 1996; Porter & Heppelmann, 2014; Xia et al, 2012). However, real use slightly decreases over the years, which might be explained by the effects of technology addiction, such as increased stress and decreased time and frequency of use (Sheth, 1981; Szmigin & Foxall, 1998).

In this study, only early adopters find a useful reason to use SCO, which consequently improves their well-being, as the literature has shown (Gonzalez et al., 2017; Van Ittersum et al., 2013). Previous research has also demonstrated that early adopters are more attracted to basic technology functions than those who have been using the product or service for a longer time (Huh & Kim, 2008). Indeed, consumers are more likely to adopt a technology if they perceive it as convenient and useful even though they do not enjoy using the technology at first (Saga & Zmud, 1994). For the early majority, the link might be non-significant because they have not made the link between using an SCO for its usefulness and the subsequent possibility that it could improve their well-being. Moreover, for the late majority, the link might become non-significant as it becomes routine to use SCO over time and the PU is less linked to well-being. We also see that PU increases over the time of use, showing that SCO

probably help users to improve their performance (Davis, 1989). Moreover, the influence of PEU on well-being slightly increases over the time of use. The more people find an SCO easy to use, the more it increases their perceived abilities and well-being (Ahmadpour et al., 2015; Fang et al., 2014; Sanzo-Perez et al., 2015).

Following the literature, the influence of PSI on perceived well-being increases over the years of use, and experience enhances users' social status within social groups (Kuisma et al., 2007; Rogers, 1983). However, when we compare the means of PSI through the stages of adoption, we find a counter-intuitive result: PSI decreases with time of use. Therefore, users perceive a less positive image from SCO over time, perhaps due to addiction effects (e.g., Gonzalez et al., 2017; Seligman, 2003).

Regarding the relationships between the TAM's main variables (e.g., real use, PU, and PEU), all the relationships are significant, positive, and increase over time, except for the influence of PU on real use among the late majority of users, which is non-significant. This goes against some research that did not find a significant link between PEU and PU (Childers et al., 2001; Dabholkar & Bagozzi, 2002) or between PEU and real use (Muk & Chung, 2005). Instead, it confirms other research that shows the significant links between the TAM's variables (Adams et al., 1992; Chen & Tan, 2004; Davis et al., 1989; Gentry & Calantone, 2002; Hong et al., 2002; Johnson & Hignite, 2000; Porter & Donthu, 2006; Rauschnabel et al., 2018; Saga & Zmud, 1994; Schepers & Wetzels, 2007; Venkatesh & Davis, 2000; Zhang & Mao, 2008). These results still posit that the TAM is a relevant model to study technology usage, including with new technologies such as SCO. PU and PEU are thus strong antecedents of technology usage (Calantone et al., 2006; Davis, 1989; Taylor & Todd, 1995. King & He, 2006; Venkatesh & Davis, 2000).

PSI's influence on the TAM's main variables (e.g., real use, PU, PEU) decreases over time of use (e.g., Muk & Chung, 2005), and it becomes non-significant with PEU for the early majority and the late majority of users. We hypothesize that this link becomes non-significant because users gain experience of use, decreasing the influence of PSI on their perceived abilities in relation to SCO (e.g., Saga & Zmud, 1994). Or else, SCO become a part of their daily life, leading to less self-image identification and thus less impact on PEU (e.g., Cowart et al., 2008; Sirgy, 1985) These results posit that social value is relevant in explaining technology usage with SCO as well (Bagozzi, 2007; Bandura, 1986; Compeau & Higgins, 1995; Venkatesh & Davis, 2000).

In this conceptual model, we add moderators for the links between the main TAM variables (i.e., PU, PEU, real use). Privacy concerns decrease through experience, probably because users learn to control their SCO and feel less scared about privacy invasion than they did at first. Utility value can compensate for privacy concerns through, for example, personalization (Dimitriadis & Kyrezis, 2010; Sirdeshmukh et al., 2002). Users then believe that the benefits of personalization are higher than the costs of privacy loss (Hong & Thong, 2013; Xu et al., 2011). Furthermore, improving social image can also compensate for the risks of privacy invasion (e.g., Dimitriadis & Kyrezis, 2010). The literature also shows that the moderating effect of privacy concerns becomes non-significant when users are aware of these risks and feel control over SCO (e.g., controlling data sharing, turning SCO off when not in use), over the management of their personal data, and over the consequences of sharing (Rauschnabel & Ro, 2016; Rauschnabel et al., 2018).

Innovativeness also plays a role in the use of SCO. It increases through the years of use, showing that with experience people feel more innovative and experts on SCO (e.g., Rogers, 1983). Furthermore, it seems that early adopters have fewer positive beliefs about SCO when they are starting to learn how to use SCO (e.g., Agarwal & Karahanna, 2000). With the early majority, innovativeness increases the influence of real use on perceived well-being, as the literature shows (e.g., Agarwal & Karahanna, 2000; Eastlick & Lotz, 1999; Goswami & Chandra, 2013; Reynolds & Ruiz De Maya, 2013). Indeed, innovators perceive more positive benefits from using SCO (Agarwal & Karahanna, 2000; Eastlick & Lotz, 1999). In addition, the late majority of users use SCO more for social reasons than usefulness, which has an influence on well-being (e.g., Higgsa & Dulewicz, 2014). As users recognize the value of a technology only after using it (Moore, 2014), the perceived benefits after trying the technology might be higher or lower according to their expectations (Jahanmir & Cavadas, 2018). In line with the literature, we posit that innovativeness should be studied as a moderator instead of a direct antecedent (Yi et al., 2006).

3.1.6. Contributions

3.1.6.1. Theoretical contributions

This research contributes to the literature in the following ways. We highlight the consequences of SCO on perceived well-being and its antecedents. Our research thus contributes to marketing and management science literature, which is lacking to explain the consequences of SCO on perceived well-being (Anderson et al., 2013; Arora et al., 2017; Kim et al., 2016; Krebs & Duncan, 2015). More specifically, we build a conceptual model with TAM's main variables (e.g., real use, PU, PEU) and PSI influencing perceived well-being. The TAM's main variables are relevant in the SCO context, and the explanatory power of the model is improved with experience of use. Privacy concerns and innovativeness are considered moderators to study their impact on the relationships between the TAM's main variables (i.e., PU, PEU, real use). We collect three sets of data over three years to differentiate early adopters, the early majority of users, and the late majority of users. Therefore, we show that the significance of the relationships between the variables depends on users' experience of use (Davis et al., 1989; Keil et al., 1995; Rogers, 2003). Moreover, we position our research in line with other research showing that smart technologies are linked to positive feelings (e.g., Atzori et al., 2010; Etzioni, 1999; Harkin et al., 2016; Kluger & DeNisi, 1996; Porter & Heppelmann, 2014; Xia et al., 2012). This study also confirms that people have different perceptions of SCO according to the adoption stage (Childers et al., 2001): in the early adoption stage, SCO are seen as useful technologies that become hedonic technologies with time. Furthermore, this research confirms privacy concerns as the main cause of stress resulting from using SCO (e.g., Buchanan & Ess, 2006; Hong & Thong, 2013). We also show that the more users feel they can control their SCO, the less they will perceive privacy concerns and the more they will perceive well-being. Finally, this study shows that innovativeness influences positive feelings toward SCO (e.g., Agarwal & Karahanna, 2000; Eastlick & Lotz, 1999).

3.1.6.2. Managerial contributions

Most managers' goal is to improve consumer well-being, and the IoT and smart technologies are a way to reach this goal (Arora et al., 2017). In order to achieve that goal, managers are looking for consumers' perceptions of smart objects and of well-being in order to understand what improves and what decreases their feelings of well-being (e.g., Verhoef et al., 2017).

Results show that at first real use has a positive influence on perceived well-being, followed by PSI and PEU. Therefore, SCO should be intuitive and easy-to-learn technologies in order to favor positive feelings (e.g., Calantone et al., 2006; Davis, 1989; Davis et al., 1989; Taylor & Todd, 1995). Then, for the early majority, PU becomes a significant antecedent of perceived well-being as well as real use, PSI, and PEU. SCO should thus give utility reasons for people to use them. Finally, for the late majority of users, PSI becomes as important as real use, showing the importance of creating a social identification between the target and SCO (e.g., Firat & Venkatesh, 1995). Furthermore, utility benefits can be improved through social benefits too (Bagozzi, 2007; Chitturi et al., 2008; Novak et al., 2000; Van der Heijden, 2004; Venkatesh & Davis, 2000). In addition, privacy concerns are the main source of stress with SCO (Bhattacharjee, 2000); therefore, companies should be transparent about data usage and security policies, in order to increase trust and more positive feelings toward the technology (Shieh et al., 2013). Finally, our study shows the importance of targeting first innovators and early adopters with rational reasons and utility benefits (Rogers, 2003; Von Hippel, 1986); then, with advancing time, social benefits become more important to increase perceived well-being. Indeed, innovative consumers play a key role in the diffusion and adoption of new technologies, including SCO (Im et al., 2003). Besides, the late majority of users are more loyal to a brand than early adopters (Meyer-Waarden & Benavent, 2003).

3.1.7. Limits and further research directions

This research is not without limitations, and there are several ways in which other researchers could address these limitations and advance this research in the future.

First, the study should be replicated with a more representative sample. Our sample comprises only French students, and it would be interesting to broaden the sample to include other generations and cultures as well (Hofstede, 2001; Straub et al., 1997).

We also have three different sets of data and it would be interesting to do a longitudinal study to follow up the same sample as perceptions can differ to individuals (e.g., Donaldson & Dunfee, 1994).

Then, our study considers all types of SCO (e.g., connected speakers, smart watches, connected lights, etc.) and could not focus on just one type of SCO, due to the small number of respondents by category of SCO. Future research should focus on only one type of SCO and differentiate the antecedents of perceived well-being according to particular SCO (Mani & Chouk, 2017).

Finally, perceived well-being does not take into account objective facts (Diener, 1984) and we have no real-time behavior indicators of perceived well-being. Therefore, cooperation projects with SCO companies are recommended to get real-time behavioral data (Ahmadpour et al., 2016).

Summary of contributions

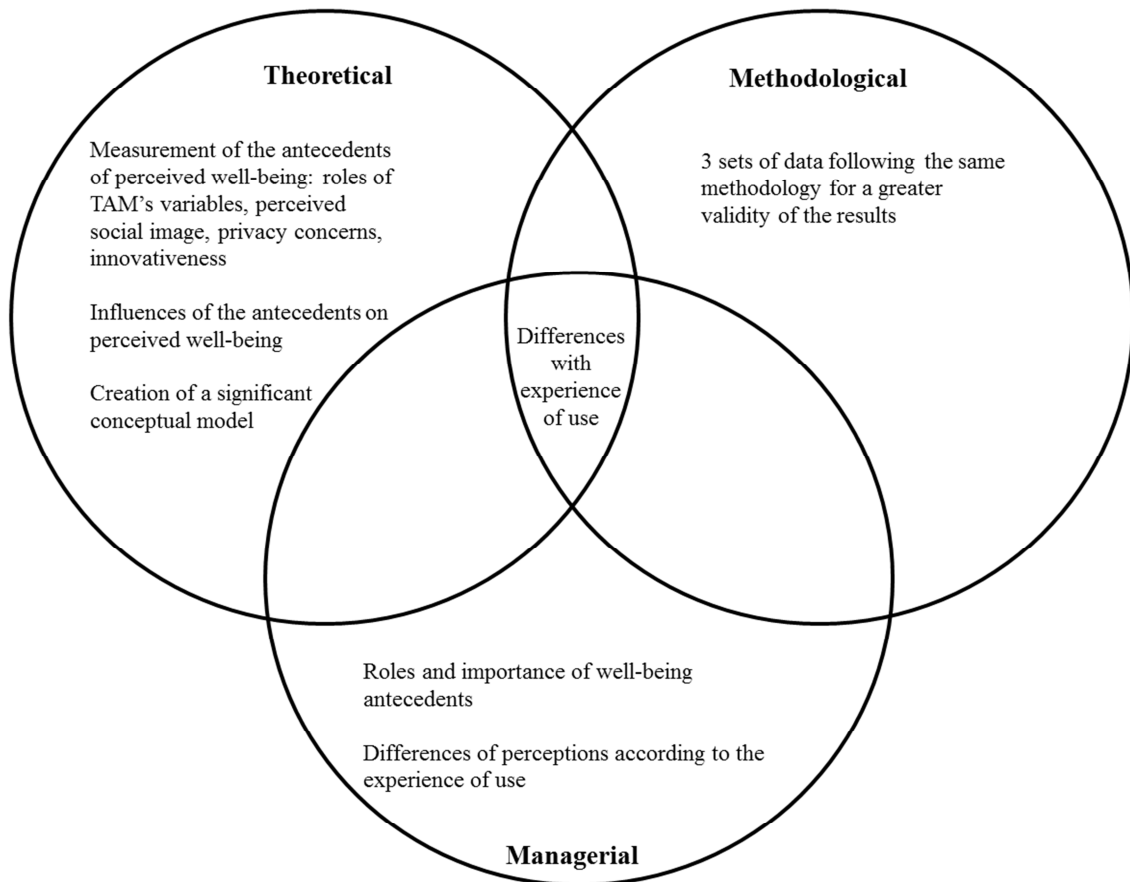


Figure 36: Summary of contributions (*Article 6; influence of SCO on well-being*)

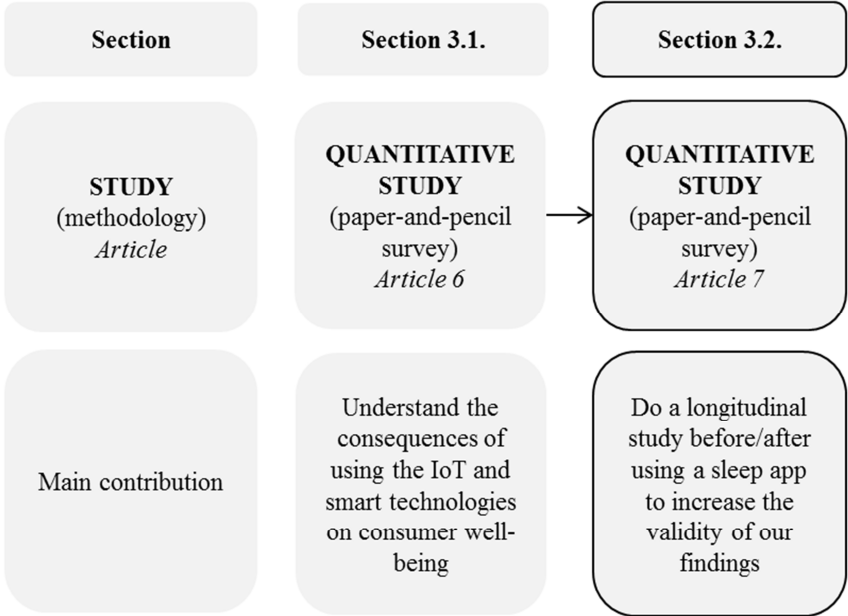
The summary of our contributions for this study (see Figure 36) shows three kinds contributions:

- (1) Theoretical contributions: we measure antecedents of perceived well-being (TAM's main variables, perceived social image, privacy concerns, innovativeness), we test the influences of these antecedents, and we create a significant conceptual model to explain the concept of perceived well-being with the SCO context;
- (2) Methodological contributions: we reproduce the same methodology with three sets of data according to the experience of use for a better understanding of well-being;
- (3) Managerial contributions: we show the importance of well-being antecedents, and the differences of perceptions according to experience of use.

Transition: from the consequences of using smart objects to using smart apps

This study aims to deepen the knowledge of previous research regarding the consequences of the IoT and smart technologies on perceived well-being. The sample is made of three sets of data (100 users using SCO at year 1, 273 users using SCO at year 2, and 222 users using SCO at year 3. Results show that real use, perceived ease of use, perceived usefulness, perceived social image, privacy concerns, and innovativeness have an influence on perceived well-being. However, one limit from this study is that we could not follow up the responses, so we have three different sets of data whereas perceptions can change with time (Reinhardt & Gurtner, 2014; Rogers, 2003), and according to individuals (e.g., Donaldson & Dunfee, 1994).

Therefore, we do a second longitudinal study and choose a sleep app easy to use, useful, with health and well-being motivations, and easily/free accessible for consumers. As already mentioned in chapter 2, a sleep app’s main goal is to improve well-being through a better sleep and quality of life. As a matter of fact, this second study should enable us to deepen the concept of perceived well-being in the context of the IoT and smart technologies. Section 3.2. presents a quantitative study which tests the influence of a sleep app on well-being before and after one week of use.



3.2. Influence of smart apps on well-being: Do digital applications improve users' feelings of well-being? (Article 7)

Abstract

Health applications are becoming popular on the application market. Most specifically, sleep applications mean to enhance users' sleep and thus health, to improve their overall well-being. This research contributes to understanding how well-being can be influenced by using a sleep application. The data is obtained from 182 respondents who tested a sleep application for one week. Structural equation modelling shows that perceived ease of use, perceived usefulness and real use have a direct influence on perceived well-being. Even though privacy concerns moderate the influences on perceived well-being and represent one of the main obstacles of using sleep applications and smart technologies, they do not have a significant direct influence on perceptions of well-being. Other factors linked to personality traits and perceived abilities about technologies moderate the influences on perceived well-being. This study aims to understand what enhance users' perceived well-being through using a sleep application.

Figure 37 sums up our main objectives and methodology for Article 7:

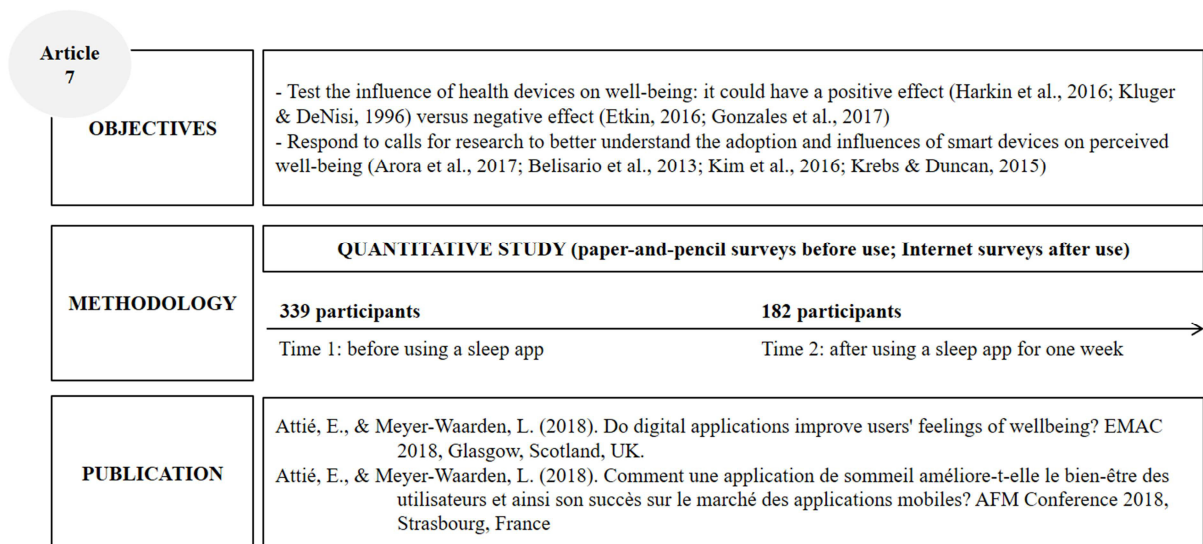


Figure 37: Main objectives and methodology (Article 7; influence of sleep apps on well-being)

3.2.1. Introduction

Mobile applications have become one of the most preferred ways to access the Internet (Lella & Lipsman, 2015). The health application market is one of the most growing application industries (Scarpelli et al., 2017). Indeed, more than 40,000 health applications are available for download (Krebs & Duncan, 2015). Therefore, it is essential for researchers to better understand why users choose a health application, and what increases loyalty of use (Kim et al., 2016).

Mobile applications are defined as software programs that collect, store and provide real-time data through smartphones or tablets to perform specific tasks (Harleen et al., 2014; Rakestraw et al., 2013). They can also automatically update their functionalities according to external indicators (e.g., sleep applications wake up users at the end of their sleep cycle, sometimes before the time set up).

Research showed that health behaviours and technology adoption are both impacted by the ease of use of self-tracking, self-knowledge, and self-management (Ahern et al., 2006; Gibbons et al., 2011; Gustafson et al., 2002). Health devices lead to important changes in health practices since users can track their real-time data (e.g., heart rate, sleep cycles, number of steps, diabetic control, prescription filling, etc.; Brennan, 1999). Indeed, this access to real-time data aims to empower users by enabling them to better control their health conditions (Demiris, 2005; Kalem & Turhan, 2015). However, the veracity and credibility of health information and privacy concerns are issues to be investigated by researchers (Krebs & Duncan, 2015). Yet, users may have difficulties to see the link between their needs and applications' functionalities (Arora et al., 2017).

Health applications target physical, mental, and spiritual health, which are also the dimensions that explain well-being in the literature (Lee et al., 2003; Sirgy, 2012). According to managers and research, health applications improve feelings of well-being (Harkin et al., 2016; Kluger & DeNisi, 1996), which is defined as a subjective state of fullness resulting from judgments, emotions and aspirations about the perception of a current situation, compared to a past or future of the person or entourage (Ayadi et al., 2019). Little is known in marketing about the experience of well-being over time although consumers often make decisions with the goal of maximizing their well-being (Mogilner et al., 2012). Besides, well-being is increasingly attracting attention from researchers and managers (Arora et al., 2017). Indeed, smart

technologies should transform the way consumers live (Porter & Heppelmann, 2014) and should enhance well-being and positive feelings (Atzori et al., 2010; Xia et al., 2012). However, Etkin (2016) showed that using smart health devices might negatively influence well-being on the long term. Since the results are mitigated and there is a lack of research on this topic, it is recommended to further study the impact of health applications on well-being (Arora et al., 2017; Kim et al., 2016; Krebs & Duncan, 2015).

Therefore, the main contribution of this paper is to study the influence of using a sleep application on users' perceptions of well-being since no research has been done in this domain, to our best knowledge. Furthermore, the relationships between TAM's main variables (real use, perceived usefulness, perceived ease of use) and perceived well-being are studied as little is known about the direction and influences between these variables (Steptoe et al., 2012). Besides, different categories of users are defined according to personality traits, personal beliefs and abilities, in order to refine targeting strategies (e.g., product development, advertising, privacy policies). To respond to these objectives, we organize a survey with 182 participants who used a sleep application for one week.

This article is organized as follows: first, the theory and conceptual framework are described in section 3.2.2.; then, the methodology and the data used are shown in section 3.2.3.; afterwards, results are presented in section 3.2.4., followed by a discussion with the theoretical and managerial implications in section 3.2.5., and by the contributions in section 3.2.6.; finally, we conclude with the limits and opportunities for further research in section 3.2.7.

3.2.2. Literature review

Based on a preliminary qualitative study (*see Article 1*), we further investigate the influence of the following variables on users' perceived well-being: perceived ease of use, perceived usefulness, real use, satisfaction of use, sleep benefits, privacy concerns, technology trust, and personality traits (e.g., a well-being personality).

Besides, the uses and gratification theory (Katz et al., 1974) is an appropriate framework for studying the use of applications. It is a predictive and explanatory theory that explains how people use media information, associating users' needs, goals, satisfaction, perceived benefits and consequences of use (West & Turner, 2010). This theory applies to sleep applications

because it responds to users' (1) cognitive needs, to obtain specific information about sleep quality and quantity; (2) affective needs, to improve sleep quality, and thus well-being and positive moods; (3) personal integrative needs, to develop an ability to use sleep applications, and improve performances; (4) social integrative needs, to obtain or establish an innovative social status; (5) tension free needs, to feel relieved from sleep tensions (Katz et al., 1974).

Furthermore, sleep applications could fit into daily routines, subsequently improving feelings of well-being (e.g., Dhar & Wertenbrach, 2000; Demiris, 2005; Kalem & Turhan, 2015; Spangenberg et al., 2003; Strahilevitz & Myers, 1998; Van der Heijden, 2004). Figure 38 presents the theoretical model before use, and Figure 39 presents the theoretical model after use. Then, our hypotheses and their justifications are subsequently presented.

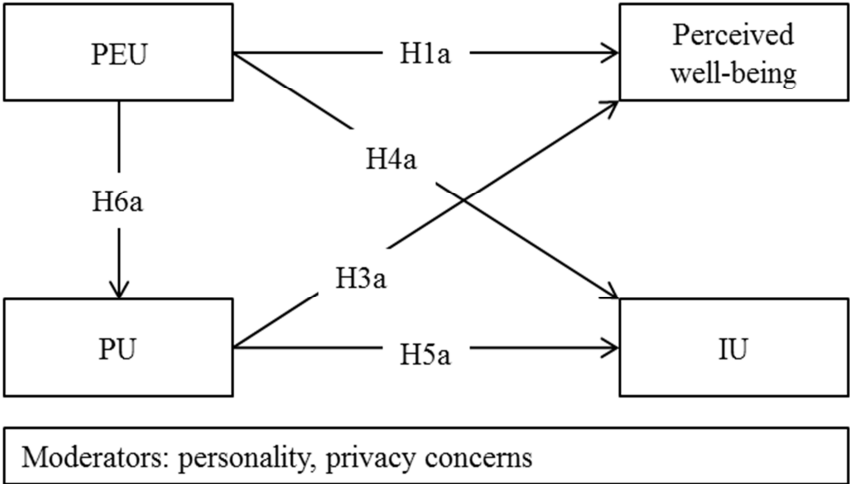


Figure 38: Conceptual model before use

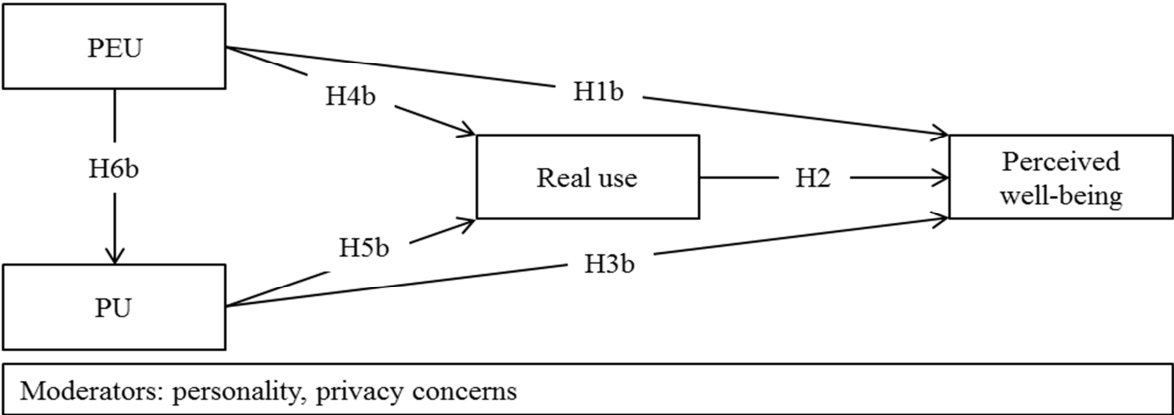


Figure 39: Conceptual model after use

3.2.2.1. The hypotheses about main effects

The use of technologies has been one of the most effective ways to enhance healthcare (Menachemi et al., 2007). The health factor is included in the concept of well-being (Sirgy, 2001) since physical, spiritual, and mental health influence overall well-being (Dolan et al., 2008; Rozanski & Kubzansky, 2005; Su et al., 2014), along with quality of life (Diener & Chan, 2011), and consumer choices (Gilovich et al., 2015). Researchers recognized the importance of consumer well-being in the literature (Su et al., 2014). Therefore, understanding its antecedents is important (Friedman & Kern, 2014). The concept of well-being defines how and why consumers perceive experiences in positive ways, through cognitive judgments and affective reactions, without objective facts (Diener, 1984). In this study, perceived well-being measures the assessment of users' experience, such as perceptions of hedonism, and improvements of their health and quality of life.

Moreover, easy-to-use technologies increase the perceived abilities of people, positively enhancing their perceived well-being (Sanzo-Perez et al., 2015). Perceived ease of use (PEU) is the degree to which the use of a technology is perceived as easy and free of efforts (Davis, 1989). The accessibility of a technology and little task complexity improve well-being (Fang et al., 2014). When the technology seems easy to use, users perceive it as more reassuring, which increases the perception of a pleasurable experience (Gu et al., 2010). However, if the technology seems too hard to use, people can feel a lack of control and knowledge, which decreases their perceived well-being with usage (Ahmadpour et al., 2016). Therefore, we hypothesize:

H1: PEU has a positive influence on well-being (a) before use and (b) after use

Smart technologies should enhance consumer well-being by improving quality of life (Atzori et al., 2010; Etzioni, 1999; Harkin et al., 2016; Kluger & DeNisi, 1996; Porter & Heppelmann, 2014; Xia et al., 2012). Indeed, a better well-being can come from the ease of use of self-tracking, self-knowledge, and of self-management of smart objects (Ahern et al., 2006; Gibbons et al., 2011; Gustafson et al., 2002). Besides, the more people use smart technologies such as sleep apps, the more they should feel senses of well-being (Davis & Pechmann, 2013). Researches have shown that using health apps should improve overall health and well-being (e.g., Demiris, 2005; Dhar & Wertenbrach, 2000; Kalem & Turhan, 2015; Spangenberg et al., 2003; Van der Heijden, 2004). Therefore, health apps should fit into

daily routines, which should subsequently improve health and well-being (e.g., Dhar & Wertenbrach, 2000; Spangenberg et al., 2003; Strahilevitz & Myers, 1998; Van der Heijden, 2004). However, other researches demonstrated different results. Etkin (2016) showed that using smart health devices decreases well-being on the long term, due to the consequences of technology dependence and stress. Gonzalez et al. (2017) demonstrated the same negative effect with mobile apps. Since the results in the literature are mitigated about the impact of smart devices on well-being, further studies are highly recommended (Anderson et al., 2013; Arora et al., 2017; Kim et al., 2016; Krebs & Duncan, 2015). Thus, we hypothesize:

H2: Real use has a positive influence on perceived well-being

Moreover, an easy access to self-knowledge and self-management improves the perceived usefulness (PU) of the technology (Katz et al., 1974). PU is the degree to which people believe that using a technology can help them to improve their performance (Davis, 1989). There is a link between usefulness and hedonism, through the experience of use (Aurier et al., 2004). Therefore, SCO should fit with daily routines, subsequently improving well-being (e.g., Dhar & Wertenbrach, 2000; Spangenberg et al., 2003; Strahilevitz & Myers, 1998; Van der Heijden, 2004). Other researches also demonstrated that the more people find a technology useful, the more they perceive well-being because it gives them a rational reason to keep on using this technology over time (Gonzalez et al., 2017; Van Ittersum et al., 2013). Thus, we hypothesize:

H3: PU has a positive influence on well-being (a) before use and (b) after use

Moreover, PU and PEU are strong determinants of technology usage (Calantone et al., 2006; Davis, 1989; Taylor & Todd, 1995). People have a more positive attitude toward a new technology when it is associated with utility benefits such as PEU (Davis, 1989; Rauschnabel et al., 2015), and thus they use it more often with experience of use (King & He, 2006; Venkatesh & Davis, 2000). As such, we hypothesize:

H4: PEU has a positive influence on (a) IU (before use) and (b) real use (after use)

H5: PU has a positive influence on (a) IU (before use) and (b) real use (after use)

According to the uses and gratification theory (Katz et al., 1974), people tend to seek for cognitive and useful needs (e.g., specific information, performance improvement,

communication, etc.) when using the media (e.g., TV, the Internet, mobile applications, etc.). Mobile applications are useful when they manipulate sensitive data such as health information to respond to specific goals (Davis, 1989). PU is the degree to which people believe that using a technology will help them to improve their performance (Davis, 1989); PEU is the degree to which the use of a technology is perceived as easy and free of efforts (Davis, 1989). Likewise, a higher PEU increases PU which both influence intentions to use since users are reluctant to make efforts in using new technologies (Davis, 1989; Rauschnabel et al., 2015; Venkatesh, 1999). Furthermore, attitudes toward a technology affect intention, which in turn influence real use (Davis, 1989). Therefore, we hypothesize:

H6: PEU has a positive influence on PU (a) before use and (b) after use

3.2.2.2. The hypotheses about moderators

Perceived well-being can be linked to cognitive and emotional reactions due to experience or specific personality traits (Diener et al., 1999; Kahneman et al., 1999). Personality traits define a specific behaviour, emotions, and values (Osgood, 1962). Consumers with specific personality traits can be more or less able to feel feelings of well-being (Csíkszentmihályi, 1975). Deriving from the theory of flow, people with a high well-being personality are more predisposed to recognize, accept, feel then share feelings of well-being thank others (Attíé & Meyer-Waarden, 2018). To them, well-being refers to a way of being, a state of the soul and a way of doing well (e.g., Guibet Lafaye, 2007). This follows the eudemonism theory linked to people's abilities and willingness to find well-being (Ryan & Deci, 2001). Users with a high well-being personality can thus perceive greater positive benefits while using a sleep application (e.g., Siu et al., 2016), leading to the following hypothesis:

H7: The effects hypothesized in H1, H2 and H3 are greater for users with a high well-being personality

Privacy concerns remain the main reticence to use smart technologies (Phelps et al., 2000). It is defined as the degree to which extent users are concerned about the flow of their information (Phelps et al., 2000). Sleep applications collect users' data during the night to wake them up at the right time (e.g., at the end of their sleep cycle). Privacy concerns arise when users are worried about the collection of personal information and how the data is used (Etzioni, 1999; Hoffman et al., 1999; Shin, 2010). Companies might sell this information to

third parties (e.g., other companies, advertisers) for marketing purposes (Hempel & Lehman, 2005) or proactively tailor their own service based on use indicators (e.g., Chellappa & Sin, 2005). Therefore, users can consider this as intrusive, arousing privacy concerns (Phelps et al., 2000). Research showed that the more people fear about privacy concerns, the less they intend to use technologies, because it increases stress and negative feelings (Dimitriadis & Kyrezis, 2010). Thus, we hypothesize:

H8: The effects hypothesized in H1, H2 and H3 are lower for users with high privacy concerns

3.2.3. Methodology

Among the different types of mobile applications in the health field, we study a sleep application. The sleep application chosen is free since price should not influence use (Kim et al., 2016).

3.2.3.1. Description of the scales

The variables were measured with validated scales from prior research that we adapted to our context of study (e.g., ‘This sleep app is easy to use’). To measure real use, we selected the scale from Chau (1996); for perceived usefulness and perceived ease of use, we chose Davis’ (1989) scale; for perceived well-being, we adapted a scale Munzel et al. (2018), Brief and Aldag (1977), Howie et al. (1998) and Diener et al. (1985); for privacy concerns, we used the scale from Hong and Thong (2013); and, to measure the well-being personality, we used a scale to define people’s temperaments inspired by Hock’s (1962) description of sanguine people (close to the personality of high-wellbeing users) and melancholic people (close to the personality of low-wellbeing users), Csíkszentmihályi’s (1975) description of autotelic people (close to high-wellbeing users), and Harris and Westin’s (1991) description of privacy fundamentalists (close to low-wellbeing users).

The constructs were measured with existing and adapted Likert scales from prior research ranging from 1 (strongly disagree) to 5 (strongly agree).

3.2.3.2. The administration of the survey and sample

This study is conducted from October 2016 to March 2018, in a French university classroom setting with paper-and-pencil surveys. It is known that samples drawn from students facilitate comparability (Douglas & Craig, 1984). Besides, students play an important role in the development and adoption of smart devices (Barbosa et al., 2018). First, the functionalities of the sleep app are presented then students respond to a survey before using the app. Afterwards, they are asked to use the app for one week, and they are asked to respond to a second survey after use. Each respondent has an identification number to track each response before and after use. Of the 339 students that responded to the survey before use, 182 responses are valid after use (72% women; Mean age = 20.4; SD = .82). The sample size has a satisfying representativeness compared to the number of items used (Hinkin, 1995).

3.2.3.3. The reliability and validity of the items and scales

To validate the scales and keep or discard items, we used factor loadings and means by variable which show how much a factor explains a variable (i.e., factor loadings > .70; Anderson & Gerbing, 1988), the Cronbach α to show the reliability of the psychometric test (i.e., Cronbach α > .70; Nunnally, 1978), and the average variance extracted (AVE) for construct reliability (i.e., AVE scores > .50; Fornell & Larcker, 1981). Scales show a good reliability and validity in the context of sleep applications and the variables meet the necessary conditions of normality for regressions. The final items, scales and reliability indicators are detailed in Table 44.

Variable (scale reliability indicators)	Factor loadings	
	Before use	After use
Perceived well-being (Before use: Cronbach α = .89, AVE = .70, Mean = 2.44; After use: Cronbach α = .90, AVE = .73, Mean = 1.74)		
I feel good using iSommeil	.78	.88
iSommeil makes me feel happy	.78	.81
iSommeil improves my health and sleep conditions	.84	.82
iSommeil improves my quality of life	.87	.88
In general, I feel well with iSommeil	.90	.88
	Mean	.83
		.85

Variable (scale reliability indicators)	Factor loadings	
	Before use	After use
Intention to use (Before use: Cronbach α = .86, AVE = .70, Mean = 2.56)		
Regarding its advantages, I intend to use iSommeil	.89	
If I have access to similar apps like iSommeil, I will use them	.84	
Since I have access to iSommeil, I will use it	.86	
Mean	.86	
Real use (After use: Cronbach α = .94, AVE = .83, Mean = 2.52)		
I use a lot iSommeil		.93
I use iSommeil in my daily life if possible		.93
I use frequently iSommeil		.88
I use iSommeil in my daily life when needed		.92
Mean		.91
Perceived ease of use (Before use: Cronbach α = .83, AVE = .60, Mean = 3.78; After use: Cronbach α = .90, AVE = .84, Mean = 3.59)		
It seems easy to use iSommeil	.86	.92
Using iSommeil seems clear and understandable	.84	.90
It is easy for me to become competent at using iSommeil	.87	.91
Mean	.86	.91
Perceived usefulness (Before use: Cronbach α = .90, AVE = .84, Mean = 2.77; After use: Cronbach α = .90, AVE = .84, Mean = 1.67)		
iSommeil is good at assisting me in my daily life	.94	.92
iSommeil makes my life easier	.90	.91
iSommeil seems very useful to me	.90	.93
Mean	.91	.92
Privacy concerns (Before use: Cronbach α = .90, AVE = .72, Mean = 3.06; After use: Cronbach α = .89, AVE = .71, Mean = 2.99)		
I am afraid iSommeil can collect my data	.87	.89
I am afraid about the type of data iSommeil collects about me	.85	.86
It bothers me that iSommeil collects my personal data	.88	.86
I fear iSommeil uses my data for other purposes	.82	.85
Mean	.85	.86

Variable (scale reliability indicators)	Factor loadings	
	Before use	After use
Well-being personality (Before and after use: Cronbach $\alpha = .70$, AVE = .62, Mean = 3.72)		
I often feel full of positive energy		.84
I often generate lots of enthusiasm		.78
I am sociable and open to others		.73
	Mean	.78

Table 44: Scales reliability indicators (*Article 7; influence of sleep apps on well-being*)

Then, we assess discriminant validity with the square root of AVE for each variable. The bold numbers along the diagonal represent the square root of AVE, and the elements off diagonal represent the inter-scale correlations (Table 45).

Before use				
Constructs	Well-being	IU	PEU	PU
Well-being	.84			
IU	.54**	.84		
PEU	.14ns	.14ns	.77	
PU	.66**	.65**	.19ns	.92
After use				
Constructs	Well-being	Real use	PEU	PU
Well-being	.85			
Real use	.73**	.91		
PEU	.29**	.33**	.92	
PU	.74**	.84**	.31**	.92

** indicates $p\text{-value} < .01$; ns indicates non-significant; IU stands for intention to use, PEU for perceived ease of use, PU for perceived usefulness.

Table 45: Correlations of the latent variables (*Article 7; influence of sleep apps on well-being*)

Table 45 shows that the square root of AVE for each construct is higher than the correlations on corresponding row and column and greater than .50, showing good discriminant validity (Fornell & Larcker, 1981).

3.2.3.4. Differences of means

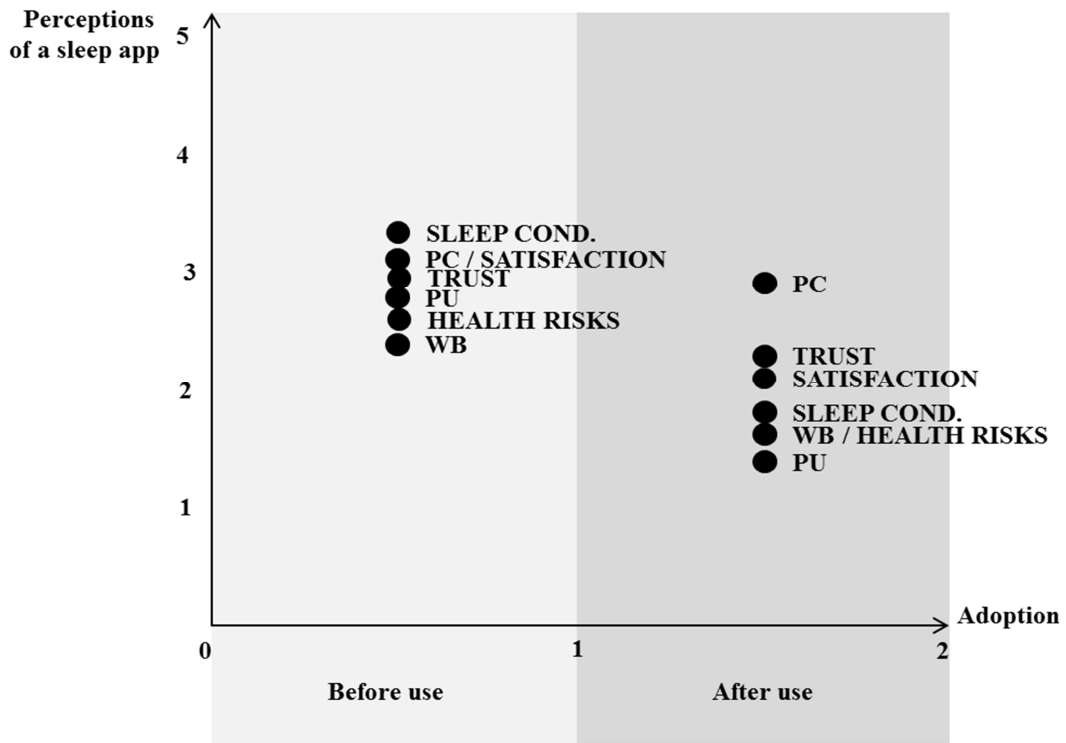
Table 46 presents the differences of means before and after use. We use the Levene's test, which evaluates the equality of variance. It indicates that when p-values are below .05, the variances are significantly different. We also measured other variables with one item, according to our preliminary qualitative study: sleep conditions, health risks, technology trust, and satisfaction of use.

Construct	Mean		F (p-value)
	Before use	After use	
Perceived well-being	2.44	1.74	7.87 (.001)
Perceived ease of use	3.78	3.59	3.43 (.035)
Perceived usefulness	2.77	1.67	19.15 (.001)
Privacy concerns	3.06	2.99	11.37 (.001)
Sleep conditions	3.10	1.76	11.38 (.001)
Health risks	2.59	1.75	8.82 (.001)
Technology trust	2.96	2.25	8.60 (.001)
Satisfaction of use	3.18	2.16	24.65 (.001)

Table 46: Differences of means (*Article 7; influence of sleep apps on well-being*)

Table 46 shows that there are significant differences before and after use with perceived well-being, PU, privacy concerns, sleep conditions, health risks, technology trust, and satisfaction of use. After use, perceived well-being decreases (M1 = 2.44; M2 = 1.74); PEU decreases (M1 = 3.78; M2 = 3.59); PU decreases (M1 = 2.77; M2 = 1.67); privacy concerns decrease (M1 = 3.06; M2 = 2.99); sleep conditions decrease (M1 = 3.10; M2 = 1.76); health risks decrease (M1 = 2.59; M2 = 1.75); technology trust decreases (M1 = 2.96; M2 = 2.25); and satisfaction of use decreases (M1 = 3.18; M2 = 2.16). The difference of PEU before and after use is not significant.

Figure 40 shows the evolution of these perceptions before then after use.



SLEEP COND stands for sleep conditions; *PC* for privacy concerns; *PU* for perceived usefulness; *WB* for well-being.

Figure 40: Perceptions of a sleep app before then after use

Figure 40 shows that the perceptions of sleep conditions, privacy concerns, satisfaction of use, technology trust, perceived usefulness, health risks, and perceived well-being decrease after use.

3.2.4. Results

3.2.4.1. Structural model testing

The data is analyzed via structural equation modelling with Analysis of Moment Structures from Statistical Package for the Social Sciences (Amos 21 from SPSS). We choose Amos since the multivariate normality analysis is acceptable (Appendix 8A²), the sample size is about 200 observations and we want to confirm theoretically assumed relationships. The estimated direct path coefficients are reported in Table 47.

	Dependent variable	Independent variable	Hypothesis	β	t-value
Before use	Well-being R ² =.68	PEU	H1a	.01	.12ns
		PU	H3a	.54	5.15***
	IU R ² =.65	PEU	H4a	.01	.18ns
		PU	H5a	.56	7.83***
	PU R ² =.19	PEU	H6a	.19	1.88**
	After use	Well-being R ² =.77	PEU	H1b	.04
Real use			H2	.41	2.76**
PU			H3b	.43	3.39***
Real use R ² =.71		PEU	H4b	.07	1.33ns
		PU	H5b	.70	13.57***
PU R ² =.31		PEU	H6b	.31	3.03**

*** indicates p -value < .001; ** p -value < .01; * p -value < .1; ns = non-significant

Table 47: Results of the estimated direct path coefficients (*Article 7; influence of sleep apps on well-being*)

² A multivariate normality test is done to check if the data has a normal distribution. The PP-plots of the data is shown in Appendix 8A. Although a considerable amount of the data in the PP-plots appears to fall on a straight line, the data is acceptable for analysis (Chambers et al., 1983). Skewness and Kurtosis indicators are in between -2 and 2, showing a normal univariate distribution (George & Mallery, 2003).

Table 47 indicates that the predictive power of perceived well-being is greater after use than before use (R^2 (before) = .68; R^2 (after) = .77), followed by the predictive power of real use (R^2 (before) = .65; R^2 (after) = .71), then of PU (R^2 (before) = .19; R^2 (after) = .31).

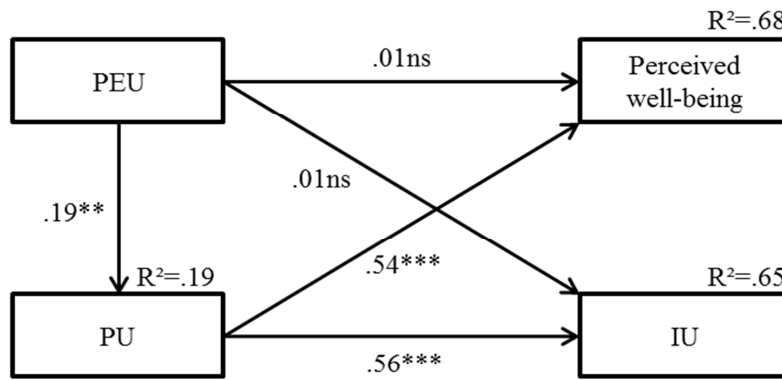
Regarding the mediating effects, PEU has no significant influence on perceived well-being before and after use (respectively $\beta = .01ns$; $\beta = .04ns$); H1a and H1b are not supported. Real use has a positive influence on perceived well-being ($\beta = .41^{**}$); H2 is supported. PU has a positive influence on perceived well-being before use ($\beta = .54^{***}$) which decrease after use ($\beta = .43^{***}$); H3a and H3b are supported. Moreover, PEU does not have a significant influence on IU and on real use (respectively $\beta = .01ns$; $\beta = .07ns$); H4a and H4b are not supported. PU has a positive influence on IU ($\beta = .56^{***}$) which increases after use on real use ($\beta = .70^{***}$); H5a and H5b are supported. Finally, PEU has a positive influence on PU before use ($\beta = .19^{***}$) which increases after use ($\beta = .31^{***}$); H6a and H6b are supported.

Furthermore, the factorial invariance analysis shows acceptable model fit indicators (Table 48) with $\text{Chi}^2/\text{DF} < 5$ (Byrne, 2006), $\text{RMSEA} < .08$ (Browne & Cudeck, 1993), $\text{CFI} > .80$ (Bentler, 1990), and $\text{TLI} > .80$ (Bentler & Bonett, 1980).

	Chi²/DF	RMSEA	CFI	TLI
Before use	4.45*	.10	.97	.89
After use	2.01*	.06	.99	.96

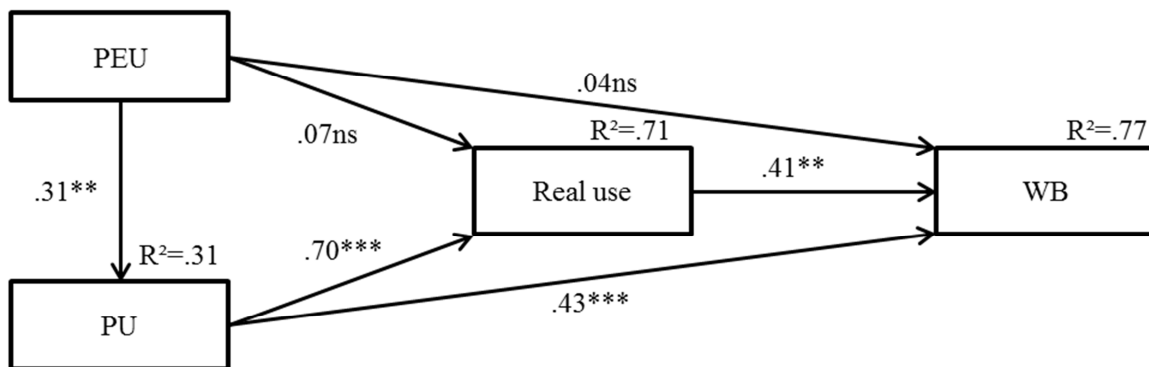
Table 48: Model fit indicators (*Article 7; influence of sleep apps on well-being*)

Figure 41 sums up the results obtained from the structural model testing before use, and Figure 42 sums up the results obtained from the structural model testing after use.



Chi²/DF=4.45*; RMSEA=.10; CFI =.97; TLI = .89
 * indicates *p-value*<.005

Figure 41: Conceptual model and model fit indicators before use



Chi²/DF=2.01*; RMSEA=.06; CFI =.99; TLI = .96
 * indicates *p-value*<.005

Figure 42: Conceptual model and model fit indicators after use

3.2.4.2. Moderating effects

To test the moderating effects, Process model 1 from Hayes is used. Process is a regression path analysis modelling tool widely used in research for estimating moderation effects (Hayes et al., 2017). Table 49 presents the main moderating effects. See Appendix 8B for the details.

H7 Moderator: Well-being personality			
	H1 PEU->WB	H2 IU->WB	H3 PU->WB
Before use	not significant	positive effect $\Delta R^2=1\%$	positive effect $\Delta R^2=2\%$
After use	not significant	not significant	not significant
H8 Moderator: Privacy concerns			
	H1 PEU->WB	H2 Real use->WB	H3 PU->WB
Before use	not significant	negative effect $\Delta R^2=1\%$	negative effect $\Delta R^2=2\%$
After use	not significant	not significant	not significant

IU stands for intention to use, PU stands for perceived usefulness, PEU for perceived ease of use, WB for perceived well-being

Table 49: Main moderating effects (*Article 7; influence of sleep apps on well-being*)

Table 49 indicates that a well-being personality positively moderates the influence of PU on perceived well-being ($\Delta R^2 = 2\%$) and of IU on well-being ($\Delta R^2 = 1\%$) only before use; H7 is partly supported. As well, privacy concerns moderate the influence of real use on perceived well-being ($\Delta R^2 = 1\%$), and of PU on perceived well-being ($\Delta R^2 = 2\%$) only before use; H8 is partly supported.

3.2.4.3. Control variables

In line with the literature, it is advisable to include control conditions to provide a stronger test of the hypotheses. We decided to add these control variables: gender (Gefen & Straub, 1997; Venkatesh & Morris, 2000), positive and negative moods and emotions (Parrott & Hertel, 1999; Snyder & White, 1982), and innovativeness (e.g., willingness to adopt new things; Rogers, 1983). Table 50 presents the tests of the control variables.

	R²	ΔR²	F (p-value)
Before use			
Without control variables	.68		
With gender	.68	0%	18.85 (.001)
With positive moods	.68	0%	18.68 (.001)
With negative moods	.68	0%	18.55 (.001)
With innovativeness	.68	0%	18.54 (.001)
After use			
Without control variables	.77		
With gender	.77	0%	32.56 (.001)
With positive moods	.77	0%	32.24 (.001)
With negative moods	.77	0%	32.87 (.001)
With innovativeness	.76	0%	31.60 (.001)

Table 50: Control variables (*Article 7; influence of sleep apps on well-being*)

Table 50 shows that gender, positive or negative moods, and innovativeness are not significant predictors of the model.

3.2.5. Discussion

One of our theoretical goals is to study the consequences of real use, PEU and PU as direct predictors of perceived well-being, as well as well-being personality and privacy concerns as moderators. This study examines how sleep apps influence feelings of well-being before then after use, in order to see if consumers' expectations are met. The conceptual model shows a good fit according to literature standards (Wheaton et al., 1977) and it improves once respondents have tried the sleep application. This follows the disruptive innovation theory, which says that experience of use positively changes consumer perceptions (Huh & Kim 2008; Reinhardt & Gurtner, 2014).

In line with existing literature, perceived well-being is positively influenced by real use and perceived usefulness (e.g., Etzioni, 1999; Katz et al., 1974; Kawachi et al., 2007; Van der Heijden, 2004; Yip et al., 2007). More specifically, the influence of real use on perceived well-being is significant, as in the literature (Atzori et al., 2010; Etzioni, 1999; Harkin et al., 2016; Kluger & DeNisi, 1996; Porter & Heppelmann, 2014; Xia et al., 2012). The significant influence of PU on real use and on perceived well-being follows the uses and gratification theory (Katz et al., 1974) which shows that consumers seek for useful needs when using the media such as mobile apps. However, PU decreases after use, showing that the sleep app probably did not enable users to improve their sleep (Davis, 1989), that the sleep app did not allow a better self-knowledge and self-management (Katz et al., 1974), or that our sample did not have a specific goal linked to their sleep conditions (Davis, 1989). Also, PEU has no significant influence on perceived well-being, showing that the sleep app probably did not increase the perceived abilities of people (Sanzo-Perez et al., 2015) or seemed too hard to use, enhancing a lack of control (Ahmadpour et al., 2016; Fang et al., 2014). After comparing the differences of means of perceived well-being and sleep conditions, we posit our study on the side of the literature, which says that sleep apps can decrease well-being after use (Etkin, 2016; Gonzalez et al., 2017).

Concerning the TAM's main variables, PEU only influences PU, as in theory (Davis, 1989; Rauschnabel et al., 2015; Venkatesh, 1999). This follows one side of the theory saying that PU is more important when studying new technologies (Van der Heijden & Verhagen, 2004). Even though there are more studies confirming significant links between the TAM's main variables (Schepers & Wetzels, 2007), other researches also find no significant link between

PEU and real use (Muk & Chung, 2005). Our hypothesis is that PEU is relevant with new technologies and even though sleep apps might be considered as new technologies since it uses the IoT technology, people are used to smartphones so it does not seem to be a disruptive technology. Easy to use technologies still seem to be more useful since it costs less time and efforts to learn and to use (Davis, 1989).

Moderators of the links between perceived well-being and its antecedents show that a well-being personality and privacy concerns have an influence only before use. People that rate higher on a well-being personality, as defined in this study, have better abilities to recognize, accept and feel these senses of well-being rather than those who rate lower on the well-being personality. A sleep app might be considered as a hedonic/health technology, which can explain this result. It also shows that perceived well-being is linked to personality traits, confirming theory (Csíkszentmihályi, 1975; Diener et al., 1999; Kahneman et al., 1999). Moreover, privacy concerns negatively influence the strength of IU or real use, and the strength of PU on perceived well-being. Privacy concerns slightly decrease after use, probably because users feel they control the sleep application and feel less scared about privacy invasion than at first. It seems that PU cannot compensate privacy concerns so the personalisation benefits might be too low next to the privacy loss (Dimitriadis & Kyrezis, 2010; Hong & Thong, 2013; Sirdeshmukh et al., 2002; Xu et al., 2011). Indeed, collecting the data while users sleep can be perceived as too intimacy and intrusive, arousing privacy concerns (Phelps et al., 2000), stress and negative feelings (Dimitriadis & Kyrezis, 2010). Literature also showed that the moderating effect of privacy concerns becomes non-significant when users are aware of these risks and feel control over the technology (Rauschnabel & Ro, 2016; Rauschnabel et al., 2018).

3.2.6. Contributions

3.2.6.1. Academic contributions

Consumer well-being has received little attention in marketing research (Lee et al., 2003; Moisisio & Beruchashvili, 2010). Although few studies investigated the effects of using mobile and smart technologies on perceived well-being and related outcomes, results are mitigated and the direction of the relationship continues to need clarification (Munzel et al., 2018; Steptoe et al., 2012). The literature about new technology adoption still contributes little to the knowledge about well-being (Hall & Khan, 2002). Therefore, we test the influence of using a sleep application on perceived well-being to contribute to this research gap. The model shows that PU, real use, and PEU (through PU) are important antecedents of perceived well-being. Yet, the relationship between real use and perceived well-being can go both ways: adoption can influence positively perceived well-being and perceived well-being can influence subsequently intentions and adoption (e.g., Steptoe et al., 2012).

Concerning the moderating effects, people with a high well-being personality are more predisposed to feel perceptions of well-being while using the application than others. This result suggests that people predisposed to recognize, accept, feel then share feelings of well-being felt higher positive feelings with a sleep application than others. The match between personality and the perception of digital entity has a significant effect on whether or not the user is willing to become emotionally attached to this technology (Wang et al., 2016). Attachment is a strong connection between a person and a specific thing (Malär et al., 2011). Therefore, people with a high well-being personality have a higher attachment to this kind of digital technology, perhaps because it is perceived as more hedonic than useful.

Concerning privacy concerns, the influence might be non-significant after use because many consumers are uncertain about how the mobile application really deals with their information (Sheehan & Hoy, 1999). A certain amount of uncertainty is created, as they believe they cannot always control how their information is collected, stored, shared, and used by applications (Joinson et al., 2010). Privacy concerns are also evaluated according to people's perceptions and values so it may vary with other technologies (Donaldson & Dunfee, 1994; Malhotra et al., 2004). Furthermore, more and more users are willing to give up privacy simply to try a new experience (Turow et al., 2008). Nevertheless, not considering privacy concerns in the model decreases the model fit and beyond that, little research has focused on

privacy concerns in the context of smart devices yet (Fox & Royne, 2018; Verhoef et al., 2017).

3.2.6.2. Managerial contributions

Our main managerial recommendation is that privacy concerns remain the primary obstacle to adoption, enhancing consumer reluctance. The security of the data must be a central topic in product development, data policies and communication, in order to increase trust (Bhattacharjee, 2000; Hengstler et al., 2016; Shieh et al., 2013). More specifically, sleep applications should be transparent about the way the data is collected, stored, and used. However, existing research showed that, even if users are concerned about privacy issues, they still use the technology if they believe the benefits of personalization are higher than the privacy loss (Xu et al., 2011). Consequently, sleep applications should be driven by real needs (e.g., improve sleep conditions, manage sleep time and cycles, etc.), giving at the right time the right information (e.g., number and time of deep and restless sleep cycles). Thereby, sleep applications could communicate about their utility and ease-of-use functionalities in order to attract potential users (e.g., Chang et al., 2005; Szajna, 1996) as well as their hedonic and health benefits (Deci & Ryan, 2002). Intuitive and easy-to-use mobile applications thus accelerate the adoption process. Simplifying self-tracking, self-knowledge, and self-management should enable people to easily track their information and manage their sleep, improving overall well-being and thus loyalty of use. Furthermore, studies showed that providing resources and power to users could influence their preferences and behaviors toward a technology (e.g., Fuchs et al., 2010). In this study, users appear to have felt a small sense of power, while using the sleep application. Finally, advertising and targeting should focus on traits of personality and needs (e.g., improving sleep and health).

3.2.7. Limits and further research directions

Our research is not without limits. First, the study should be replicated with a more representative sample and with other cultures and countries to increase the generality of the findings (Bianchi & Andrew, 2012; Colton et al., 2010).

Furthermore, research has shown that intention to use and adoption might change over time (Ashraf et al., 2014; Davis et al., 1989; Keil et al., 1995). Therefore, doing the same experimentation over a longer period might reveal changes in the main and the moderating effects (e.g., Etkin, 2016). Future research should thus test to which extent sleep apps enhance positive health and sleep practices on a longer term (e.g., months to years). Besides, this could give insights to companies to know the right moment to re-target users and improve loyalty of use.

Moreover, future research should compare results with different sleep applications to understand which features are the most attractive or if there is a difference between free and paid applications (Kim et al., 2016).

Other antecedents should be deepened such as sleep conditions, health risks, technology trust, and satisfaction of use. Besides, according to the flow theory (Csikszentmihályi, 1975), personalities could also depend on social factors. Therefore, future research could focus on the extent to which social circles influence technology use, perceptions of well-being, or empowerment through quantified-self.

Summary of contributions

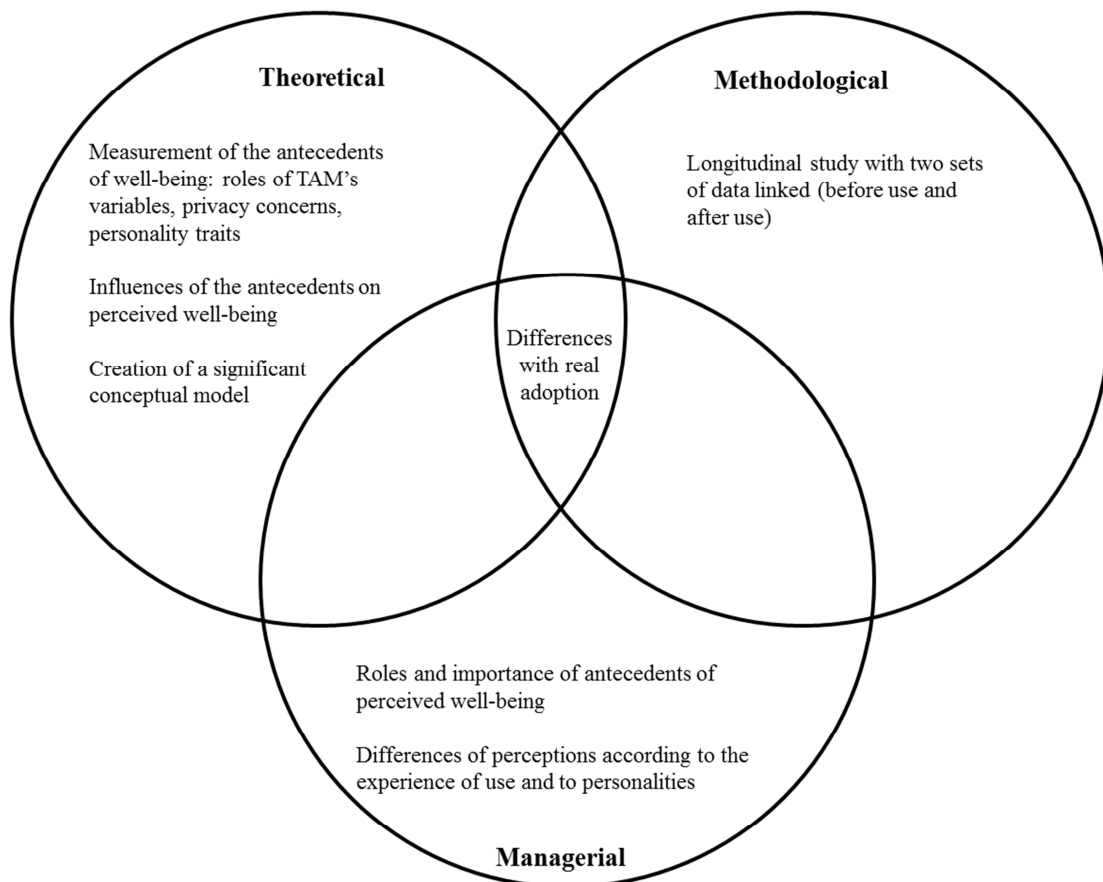


Figure 43: Summary of contributions (*Article 7; influence of sleep apps on well-being*)

The summary of our contributions for this article 7 (Figure 43) shows three kinds contributions:

- (1) Theoretical contributions: we measure the consequences of a sleep application on perceived well-being to create a significant conceptual model and better understand this concept;
- (2) Methodological contributions: we do a longitudinal study (before use and after use) to better understand the influences of the antecedents;
- (3) Managerial contributions: we highlight the roles and importance of different antecedents of adoption, as well as different personalities to redefine targeting strategies.

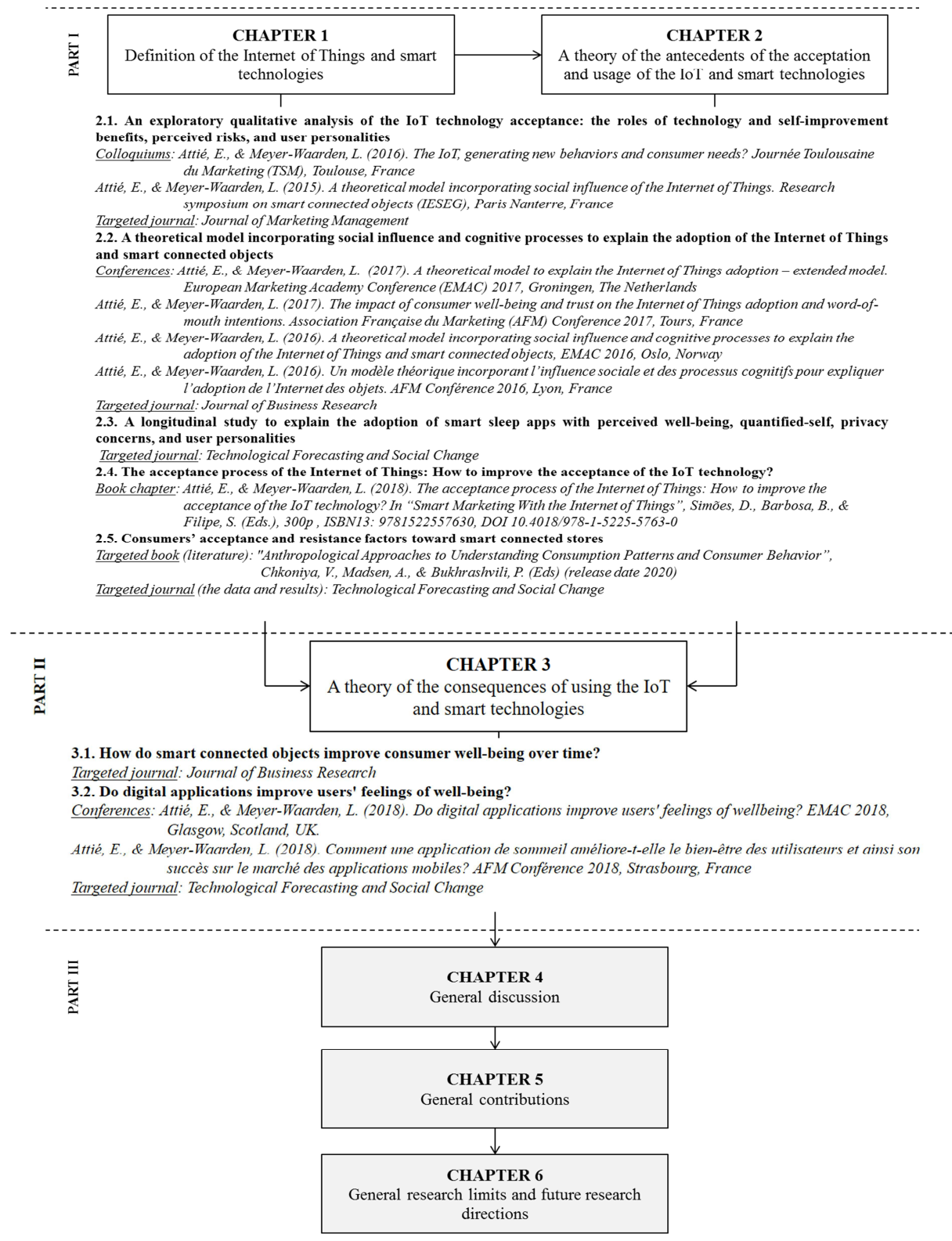
Conclusion to Chapter 3

Consumer well-being is becoming a highly attracting topic in research (Arora et al., 2017; Kim et al., 2016; Krebs & Duncan, 2015). As the primary goal of the IoT and SCO is to improve well-being (Porter & Heppelmann, 2014), these articles aim to study the influence of using SCO and a sleep app on perceived well-being. In the literature, Etkin (2016) and Gonzalez et al. (2017) showed a negative influence of smart technologies on well-being on the long term. Results of this chapter 3 differ according to the technology (i.e., SCO, a sleep app) and it should enhance the understanding of perceived well-being. Table 51 summarizes the antecedents of perceived well-being, by order of importance with 1 = high importance.

Technology	Antecedents	Influence on perceived well-being
Smart connected objects	<u>Early adopters:</u> Real use (1); PSI (2); PEU (3) <u>Early majority of users:</u> Real use (1); PSI (2); PU (3); PEU (4) <u>Late majority of users:</u> Real use / PSI (1); PEU (2); PU (3)	Experience of use decreases privacy concerns and increases perceived well-being
Sleep app	<u>Time 1:</u> PU (1); IU (2) <u>Time 2:</u> PU (1); Real use (2)	In general, a sleep app decreases feelings of well-being, increasing stress (mainly due to a low perceived usefulness and high privacy concerns) It depends on personality traits: people with a higher well-being personality feel more well-being with a sleep app than those with a lower well-being personality

Table 51: Summary of Chapter 3

PART III



Introduction to Part III

The major goal of this thesis is to deepen the understanding of the acceptance and adoption processes of the IoT and smart connected technologies, as well as the related consequences on perceived well-being. To do this, four contexts of study are explored: smart connected objects, smart sleep apps, smart homes, and smart stores. We began with qualitative exploratory studies on these contexts of study, and then we conducted quantitative studies to build conceptual models according to our qualitative findings and the literature. The results show that technology benefits are the first factors that enable technology acceptance through the classical TAM variables of perceived usefulness and perceived ease of use; subsequently, self-improvement, through perceived social image and well-being benefits, are the reasons to continue using the IoT and smart technologies. Further, perceived risks and fears about the way the data is used are the main barriers to using the IoT and smart technologies. Acceptance and adoption also depend on users' personality traits, as each consumer is unique and, thus, their perceptions differ as well. Chapter 4 sums up the discussion of the results of all our studies.

Chapter 5 examines the overall theoretical, methodological, and managerial implications of this thesis and all its studies. The contributions of our studies are put into perspective with respect to other researches on the IoT and smart technologies as well as on perceived well-being. Therefore, this chapter sums up the contributions from the different studies included in this thesis.

Finally, chapter 6 presents the overall limits and future research directions of this doctoral work.

CHAPTER 4: GENERAL DISCUSSION OF THE RESULTS

The goal of this thesis is to study the acceptance and adoption of the IoT and smart technologies as well as the consequences of using these technologies. To do this, we clarify the concept of the IoT and its components, as well as the concept of perceived well-being. The discussions from our articles are summed up in this chapter. Firstly, in section 4.1., we discuss the results linked to acceptance and adoption. Secondly, in section 4.2., we discuss the results regarding the consequences of perceived well-being.

4.1. Antecedents of adoption or rejection of the IoT and smart technologies

Results show that consumers are attracted to different aspects of the IoT and smart technologies: rational reasons (i.e., usefulness and ease of use), emotional reasons (i.e., well-being and perceived stress), social benefits (i.e., social image and status), and security with privacy concerns (i.e., the data management). Besides, it is interesting to understand the roles of each antecedent according to the stage of adoption: acceptance (before use), then adoption, appropriation, and real use (after use).

4.1.1. Antecedents of adoption

Our studies highlight the relevance of the TAM (Davis, 1989) in the context of the IoT and smart technologies. The main variables of the traditional TAM—namely, perceived usefulness (PU), perceived ease of use (PEU), and intention to use (IU)—are important antecedents of acceptance, as shown in the literature (Calantone et al., 2006; Davis, 1989; Hauser & Simmie, 1981; Taylor & Todd, 1995). It seems to be common sense to study the TAM in relation to the adoption of IoT technologies, as it is still one of the most influencing theories of human behavior (King & He, 2006; Venkatesh et al., 2003). Meta-analyses on the TAM show a robust, significant, and powerful model with strong psychometric properties that can be applied to different technological contexts (Adams et al., 1992; Bagozzi et al., 2000; Bruner & Kumar, 2005; Chau, 1996; Davis, 1989; Davis et al., 1989; Davis et al., 1992; Hu et al., 1999; Jang & Noh, 2011; Kim et al., 2009; King & He, 2006; Lederer et al., 2000; Legris et al., 2003; Mathieson, 1991; Muk & Chung, 2005; Pikkarainen et al., 2004; Ramayah et al., 2002; Taylor & Todd, 1995; Venkatesh & Davis, 1996; Wu & Wang, 2005). Furthermore, our models show a satisfying fit according to literature standards. The differences between the

adoption stages confirm the results of literature that indicate that new technology adoption is a temporal sequence of stages (Huh & Kim, 2008). Self-improvement and well-being benefits are relevant antecedents of technology acceptance and adoption in consumer contexts as well (Bruner & Kumar, 2005; Childers et al., 2001; Dabholkar & Bagozzi, 2002; Hirschman & Holbrook, 1982; Kim & Forsythe, 2008; Kulviwat et al., 2007; Van der Heijden, 2004). Finally, we followed the social cognitive theory, which indicates that technology adoption is impacted by social image (Bandura, 1986; Compeau & Higgins, 1995). Table 52 presents the results of our previous studies and the research in literature following our results.

Our results (context)	Literature	Justification
- Significant influence of IU on real use (<i>sleep apps, SCO with the early majority and late majority of users</i>)	Dabholkar & Bagozzi, 2002; Davis, 1989; Lucas & Spitler, 1999; Mohd Suki & Mohd Suki, 2011; Porter & Donthu, 2006; Vijayasarathy, 2004	- Positive intentions and beliefs toward a technology have positive effects on the adoption and use (Davis, 1989)
- Reduction of the predictive power of real use with experience of use (<i>SCO</i>)	Sheth, 1981; Szmigin & Foxall, 1998	- Early adopters tend to use the product or service more than others (Huh & Kim, 2008; Rogers, 1995)
- PU is the primary determinant of technology acceptance (<i>SCO, sleep apps</i>)	Childers et al., 2001; Davis, 1989; Davis et al., 1989, 1992; Muk & Chung, 2005	- PU is a powerful predictor of attitudes toward technologies (Childers et al., 2001; Porter & Donthu, 2006; Rauschnabel et al., 2018)
- For the late majority of users, PU has no more influence on adoption (<i>SCO</i>)	Bruner & Kumar, 2005; Johnson & Hignite, 2000	- Early adopters are more attracted to the basic functions of a technology than others (Huh & Kim, 2008) - PU decreases if technology does not improve performance (Davis,

Our results (<i>context</i>)	Literature	Justification
		1989), does not enable better self-knowledge and self-management (Katz et al., 1974), or when the sample does not have a specific goal linked to the technology (Davis, 1989)
<p>- The influence of PEU on PU remains significant (<i>irrespective of the technology and of the experience of use</i>)</p> <p>- PEU does not influence intention to use with the majority of late adopters (<i>SCO</i>)</p>	<p>Davis, 1989; Rauschnabel et al., 2015; Venkatesh, 1999</p> <p>Muk & Chung, 2005</p>	<p>- Based on a meta-analysis of 51 articles, Schepers and Wetzels (2007) prove the significance of PEU and PU in technology contexts</p> <p>- PEU is less important than PU once people learnt how to use a technology (Van der Heijden & Verhagen, 2004)</p>
<p>- Perceived well-being is the primary determinant of acceptance with smart environments (<i>smart homes, smart stores</i>); Perceived well-being influences use and it is the only antecedent for the late majority of users (<i>SCO</i>)</p>	<p>Bruner & Kumar, 2005; Çelik & Yılmaz, 2011; Childers et al., 2001; Chiu et al., 2014; Curran & Meuter, 2007; Dabholkar & Bagozzi, 2002; Hirschman & Holbrook, 1982; Johar & Awalluddin, 2011; Kim & Forsythe, 2008; Koufaris, 2002; Kulviwat et al., 2007; Muk & Chung, 2005; Novak et al., 2000; Pavlou, 2003; Rauschnabel et al., 2018; Sherman et al., 2001; Van der Heijden, 2004</p>	<p>- Smart technologies can create positive experiences and well-being, subsequently leading to greater adoption (Andreasen et al., 2012; Davis & Pechmann, 2013)</p>

Our results (context)	Literature	Justification
- Perceived well-being influences PEU and PU (SCO, sleep apps)	Andreasen et al., 2012; Davis & Pechmann, 2013	- Positive feelings enhance mental representations regarding the ease of use and usefulness of a technology (Andreasen et al., 2012; Davis & Pechmann, 2013)
- PSI influences acceptance and adoption (SCO, smart homes, smart stores)	Muk & Chung, 2005; Saga & Zmud, 1994; Seligman, 2003	- Technologies perceived as being socially conforming are more likely to be accepted, and usage becomes a social process (Hellström, 2004)
- PSI influences perceived well-being (SCO, smart homes, smart stores)	Hoffman, 2012; Kuisma et al., 2007; Naci & Ioannidis, 2015; Rogers, 1983	- PSI improves well-being through social satisfaction (Hoffman, 2012; Kuisma et al., 2007; Naci & Ioannidis, 2015)

Table 52: Summary of the antecedents of adoption showed in this thesis

Table 52 indicates that our main results are consistent with other researches. To start with, regarding the significance of the TAM main variables, we find a significant influence of IU on real use, in the contexts of sleep apps, and of SCO with the early majority and late majority of users only. In the same vein, the TAM showed that positive intentions and beliefs toward a technology have positive effects on the adoption and use (Davis, 1989). However, the predictive power of real use diminishes with experience of use, in the context of SCO. Literature showed that early adopters tend to use the product or service more than others (Huh & Kim, 2008; Rogers, 1995). Moreover, PU is the primary determinant of technology acceptance, in the contexts of SCO and sleep apps. Research showed that PU is a powerful predictor of attitudes toward technologies (Childers et al., 2001; Porter & Donthu, 2006; Rauschnabel et al., 2018). However, for the late majority of users, PU has no more influence on adoption. This can be explained by the fact that early adopters are more attracted to the basic functions of a technology than others (Huh & Kim, 2008). Once the technology is adopted, PU decreases if the technology does not improve performance (Davis, 1989), does not enable better self-knowledge and self-management (Katz et al., 1974), or when the user does not have a specific goal linked to the technology (Davis, 1989). Besides, the influence of

PEU on PU remains significant, irrespective of the technology and of the experience of use, following the literature (Davis, 1989; Rauschnabel et al., 2015; Schepers & Wetsels, 2007; Venkatesh, 1999). Nevertheless, PEU does not influence intention to use with the majority of late adopters in the context of SCO. Research showed that PEU becomes less important than PU once people know how to use a technology (Van der Heijden & Verhagen, 2004). Furthermore, well-being is the primary determinant of acceptance with smart environments — such as smart homes and smart stores—, or with SCO and the late majority of users. It seems that our samples believe that smart technologies can create positive experiences and well-being, subsequently leading to greater acceptance and adoption (Andreasen et al., 2012; Davis & Pechmann, 2013; Van der Heijden, 2004). Perceived well-being also influences PU and PEU, showing that positive feelings toward a technology enhance people’s mental representations regarding the ease of use of this technology (Andreasen et al., 2012; Davis & Pechmann, 2013). Finally, perceived social image influences acceptance and perceived well-being, in the contexts of SCO, smart homes, and smart stores. Technologies perceived as being socially conforming are more likely to be accepted and adopted, as usage becomes a social process (Hellström, 2004), enhancing social satisfaction (Hoffman, 2012; Kuisma et al., 2007; Naci & Ioannidis, 2015).

4.1.2. Antecedents of rejection

The IoT and smart technologies highlight some perceived risks and fears. The most important one is with regard to privacy concerns, due to the manner in which the IoT tracks and collects personal data (Awad & Krishnan, 2006; Hong & Thong, 2013; Phelps et al., 2001). It is of significant research interest to understand how to lower the anxiety related to the way the IoT handles personal data and the extent to which users are willing to share personal information (e.g., Chaudhuri & Holbrook, 2001; Shin, 2010; Verhoef et al., 2017). Table 53 presents the main discussion regarding privacy concerns.

Our results	Literature	Justification
<ul style="list-style-type: none"> - Privacy concerns negatively influence adoption (<i>SCO, sleep apps, smart homes, smart stores</i>) - Privacy concerns decrease with the experience of use (<i>SCO</i>) - The moderating effect of privacy concerns is non-significant after use or with smart environments (<i>smart homes, smart stores</i>) 	<p>Buchanan & Ess, 2006</p> <p>Hong & Thong, 2013; Xu et al., 2011</p> <p>Rauschnabel & Ro, 2016; Rauschnabel et al., 2018</p>	<ul style="list-style-type: none"> - The more users are concerned about the data flow, the less they intend to use the IoT (Connolly & Bannister, 2007). - Privacy concerns decrease when users believe that the benefits of using the technology are higher than the costs of privacy loss (Hong & Thong, 2013; Xu et al., 2011; Dimitriadis & Kyrezis, 2010) - The moderating effect of privacy concerns is non-significant when users are aware of these risks and feel like they control the technology (Rauschnabel & Ro, 2016; Rauschnabel et al., 2018)
<ul style="list-style-type: none"> - The role of health concerns highlighted in qualitative studies (<i>not significant in our quantitative studies</i>) 	<p>Myung et al., 2009</p>	<ul style="list-style-type: none"> - The media reported that the Internet radiations can cause illnesses, such as cancers (Myung et al., 2009)

Table 53: Summary of the antecedents of rejection showed in this thesis

Table 53 indicates that privacy concerns are the main risks perceived by consumers, in the context of the IoT and smart technologies. These concerns negatively influence adoption, confirming that the more users are concerned about the data collection and usage, the less they intend to use the IoT technology (Connolly & Bannister, 2007). However, privacy concerns decrease with the experience of use of SCO. This happens when users believe that the benefits of using the technology are higher than the costs of privacy loss (Dimitriadis & Kyrezis, 2010; Hong & Thong, 2013; Xu et al., 2011). We tested privacy concerns as a moderator and a mediator as its role is not clear in the literature, and we conclude that the moderating effect of privacy concerns is non-significant when users are aware of these risks and feel that they control the technology (Rauschnabel & Ro, 2016; Rauschnabel et al., 2018). On the opposite, with smart environments, the ubiquity, omnipresence and unpredictable characteristic of the IoT is a greater concern because it becomes harder, or impossible, to control the data share (Van der Hoven, 2013). Thereby, it is convenient to use privacy concerns as a moderator with tangible technologies, then as a mediator with intangible technologies or with people used to the technology. The IoT adoption thus implies the incorporation of tangible and intangible dimensions (Benamar et al., 2019).

4.1.3. The roles of personalities

Personality traits moderate the adoption process of technologies (Rogers, 1983; Midgley & Dowling, 1978; Agarwal & Prasad, 1998; Leonard-Barton & Deschamps, 1988; Mittal & Kamakura, 2001; Reinhardt & Gurtner, 2014). We study the moderating roles of innovativeness and two types of personalities: well-being and empowered personalities. Table 54 sums up the discussion about these moderating results.

Our results	Literature	Justification
- Innovativeness positively moderates the adoption (<i>SCO, sleep apps, smart homes, smart stores</i>)	Agarwal & Prasad, 1998; Leonard-Barton & Deschamps, 1988; Midgley & Dowling, 1978; Mittal & Kamakura, 2001; Reinhardt & Gurtner, 2014; Rogers, 1983	- Innovative people have more positive beliefs about technology use than non-innovative ones (Agarwal & Karahanna, 2000; Eastlick & Lotz, 1999; Goswami & Chandra, 2013; Reynolds & Ruiz De Maya, 2013)

Our results	Literature	Justification
- Innovativeness is more relevant as a moderator than direct predictor (<i>SCO, sleep apps, smart homes, smart stores</i>)	Huh & Kim, 2008; Jahanmir & Cavadas, 2018; Moore, 2014; Yi et al., 2006	- Innovativeness is said to be a relevant moderator impacting the links of the TAM variables (Agarwal & Prasad, 1998; Leonard-Barton & Deschamps, 1988; Mittal & Kamakura, 2001)
- A high empowered personality increases the likelihood of acceptance (<i>smart stores</i>)	Harris & Westin, 1991; Hock, 1962; Kozinets, 2012; Mill, 1998	- High-empowered consumers favour specific actions which improve their social image (Hellström, 2004)
- A high empowered personality decreases the likelihood of adoption (<i>sleep apps</i>)	Harris & Westin, 1991; Hock, 1962; Kozinets, 2012; Mill, 1998	- High-empowered consumers look for senses of control through technology (Kim & Kim, 2011)
- A high well-being personality increases the likelihood of adoption (<i>sleep apps</i>)	Csikszentmihályi, 1975; Hock, 1962; Mill, 1998; Olson, 1999; Zeanah & Fox, 2004	- People with a high well-being personality are predisposed to feel positive feelings more deeply than the average people (e.g., Csikszentmihályi, 1975; Zeanah & Fox, 2004) and are more attracted to health and well-being technologies (Ryan & Deci, 2001).
- A high well-being personality decreases the likelihood of accepting smart environments (<i>smart stores</i>)	Csikszentmihályi, 1975; Hock, 1962; Mill, 1998; Olson, 1999; Zeanah & Fox, 2004	- A high well-being personality might be more attracted by real social interactions than machines

Our results	Literature	Justification
		that bring fewer senses of excitement and hedonism (e.g., Mill, 1998).

Table 54: Summary of the roles of personalities showed in this thesis

Table 54 shows that personalities—such as innovativeness, a well-being personality, and an empowered personality—moderate the adoption process of the IoT and smart technologies. According to the technology, certain personalities will be a better match for adoption than others (Scherer, 1986). We find that innovativeness positively moderates the adoption, irrespective of the technology and of the experience of use. This follows other researches, which showed that innovative people have more positive beliefs about technology use than non-innovative ones (Agarwal & Karahanna, 2000; Eastlick & Lotz, 1999; Goswami & Chandra, 2013; Reynolds & Ruiz De Maya, 2013). Moreover, innovativeness is more relevant as a moderator than as a direct predictor, as in the literature (Agarwal & Prasad, 1998; Leonard-Barton & Deschamps, 1988; Mittal & Kamakura, 2001). Then, a high-empowered personality increases the likelihood of adoption, with smart stores, confirming that high empowered consumers perform a specific action if it improves their social image (Hellström, 2004). However, this likelihood of adopting smart technologies like sleep apps is decreased with this type of personality, since it does not give them enough senses of control (Kim & Kim, 2011). Finally, a high well-being personality increases the likelihood of adoption with sleep apps since smart technologies allow users to let go instead of being in control of themselves, which is favoured by these personalities (Hock, 1962). However, a high well-being personality decreases the likelihood of accepting smart stores. This result can be explained by the fact that a high well-being personality might be more attracted by real social interactions than machines that bring fewer senses of excitement and hedonism (e.g., Mill, 1998).

4.2. Consequences of the IoT and smart technologies on well-being

The direction of the relationship between perceived well-being and adoption is not clear in the literature. The relationship between real use and perceived well-being can go both ways (Steptoe et al., 2012). On the one hand, perceived well-being can influence adoption by enhancing positive mental representations and feelings regarding the technology (Andreasen et al., 2012; Davis & Pechmann, 2013). On the other hand, adoption could also be an important predictor of perceived well-being, since the IoT and smart technologies should enhance quality of life (Bruner & Kumar, 2005; Porter & Heppelmann, 2014). Table 55 sums up the main results regarding the consequences of IoT and smart technologies on perceived well-being.

Our results	Literature	Justification
- Real use influence perceived well-being (<i>SCO, sleep apps</i>)	Ahern et al., 2006; Etzioni, 1999; Katz et al., 1974; Kawachi et al., 2007; Van der Heijden, 2004; Yip et al., 2007	- Smart technologies should enhance perceived well-being by improving quality of life (Etzioni, 1999)
- The influence of PU on perceived well-being increases with experience of use (<i>SCO</i>)	Etzioni, 1999; Katz et al., 1974; Kawachi et al., 2007; Van der Heijden, 2004; Van Ittersum et al., 2013; Yip et al., 2007	- A technology perceived as useful gives a rational reason to continue using it (Van Ittersum et al., 2013)
- The influence of PU on perceived well-being decreases after use (<i>sleep apps</i>)	Etkin, 2016; Gonzalez et al., 2017	- PU decreases if users cannot improve their performance (Davis, 1989)
- The influence of PEU on well-being increases over experience of use (<i>SCO</i>)	Ahmadpour et al., 2016; Fang et al., 2014; Sanzo-Perez et al., 2015	- Experience of use increase the ease of use of a technology, enhancing users' perceived abilities and well-being (Ahmadpour et al., 2016; Fang et al., 2014;

Our results	Literature	Justification
- PEU has no significant influence on well-being (<i>sleep apps</i>)	Ahmadpour et al., 2016 ; Fang et al., 2014	Sanzo-Perez et al., 2015). - The influence is not significant when users do not improve their performance and abilities (Sanzo-Perez et al., 2015) or when they perceive a lack of control (Ahmadpour et al., 2016; Fang et al., 2014)
- The influence of PSI on perceived well-being increases with experience of use (<i>SCO</i>)	Gonzalez et al., 2017; Seligman, 2003	- SCO can give a positive social image, thereby improving positive feelings toward the technology (Kuisma et al., 2007; Rogers, 1983)

Table 55: Summary of the consequences of IoT adoption on consumer well-being showed in this thesis

Table 55 shows that real use influence perceived well-being in the contexts of SCO and sleep apps. This confirms that smart technologies enhance perceived well-being (Etzioni, 1999). Moreover, the influence of PU on perceived well-being increases with the experience of use of SCO and decreases with sleep apps. A technology perceived as useful gives a rational reason to continue using it (Van Ittersum et al., 2013) but the technology needs to enable users to improve their performance (Davis, 1989). Besides, the influence of PEU on well-being increases over experience of use with SCO, and has no influence with sleep apps. This shows that when experience of use enhances users' perceived abilities, it enhances perceived well-being as well (Ahmadpour et al., 2016; Fang et al., 2014; Sanzo-Perez et al., 2015). To finish, the influence of PSI on perceived well-being increases with the experience of use of SCO. Thereby, SCO can give a positive social image, which improves positive feelings toward the technology (Kuisma et al., 2007; Rogers, 1983)

After this summarized discussion of our results, the next chapter presents the main implications and contributions of this thesis.

CHAPTER 5: GENERAL CONTRIBUTIONS

As research on the IoT and smart technologies in marketing is scarce (Verhoef et al., 2017), this thesis makes theoretical, methodological, and managerial contributions that are presented below. The main goal of this thesis is to study the antecedents of acceptance and adoption of the IoT and smart technologies as well as their consequences on perceived well-being. Preliminary qualitative studies have been conducted to orientate our literature review, and quantitative studies have deepened our findings. This chapter successively deals with the theoretical, methodological, and managerial contributions of our research.

5.1. Theoretical contributions

Theoretical contributions come from our definition of the IoT and smart technologies, the understanding of acceptance, adoption, and usage of the IoT and smart technologies, then the consequences on perceived well-being, by studying timely and marketing-relevant concepts, such as perceived well-being, social value, privacy concerns, and well-being and empowered personalities. These contributions are detailed below.

5.1.1. Definition of the IoT and smart technologies

A literature review is conducted using 134 articles on the IoT and smart technologies, 14 of them originating from marketing literature. Thereafter, qualitative and quantitative studies aim to define and classify the IoT as well as its components (i.e., smart/connected apps, smart/connected objects, smart environments), responding to a research call from Verhoef et al. (2017).

5.1.2. Deepen the research on IoT acceptance

IoT acceptance is first influenced by the main TAM variables (e.g., PU, PEU, IU, real use; Childers et al., 2001; Davis, 1989), then the adoption and usage are influenced by new variables—self-improvement benefits (e.g., well-being, social image, and status) (e.g., Atzori et al., 2010; Etzioni, 1999; Harkin et al., 2016; Kluger & DeNisi, 1996; Porter & Heppelmann, 2014; Xia et al, 2012); perceived risks and fears (e.g., privacy concerns, health fears with radiations and addiction effects), and personality traits (e.g., innovativeness, well-

being and empowered personalities). Results confirm that smart technologies can be considered as hedonic technologies when they improve well-being or as useful technologies when they enhance quantified self (Benbasat & Barki, 2007) and performance (Davis, 1989). Our studies reveal the relevance of the TAM and its main variables in the IoT context and with different stages of adoption (Benbasat & Barki, 2007; Chuttur, 2009; Wu & Lu, 2013). According to the context of study, studying privacy concerns as a moderator or a mediator can improve or not the model fit. With SCO and smart apps, privacy concerns are better used as moderators, whereas with smart homes and smart stores, privacy concerns are better used as mediators. We hypothesize that when users are more used to the technology (i.e., SCO, sleep app), the risk of perceived intrusion decreases (Van der Hoven, 2013), or users believe they can control the technology (Ahmadpour et al., 2016). However, with smart environments, the notion of ubiquity, omnipresence and unpredictable characteristic of the IoT is a greater concern because it becomes harder, or impossible, to control the data share (Van der Hoven, 2013).

Finally, we obtain statistically significant and consistent theoretical models (Wheaton et al., 1977), which can be applied to future research on different IoT contexts of study. Therefore, this thesis responds to research calls regarding understanding the adoption of the IoT and its smart technologies (Foroudi et al., 2018; Oh et al., 2007; Verhoef et al., 2017).

5.1.3. Consequences of the IoT and smart technologies on consumer well-being

This thesis responds to calls for research by studying the consequences of IoT and smart technologies and how they improve or worsen consumer well-being (Atzori et al., 2010) over time (Etkin, 2016), as marketing and management science literature is lacking investigations and explanations in this context (Anderson et al., 2013; Arora et al., 2017; Kim et al., 2016; Krebs & Duncan, 2015). Results show statistically significant and consistent theoretical models (Wheaton et al., 1977), which can be applied in future research regarding IoT and smart technologies contexts and consumer well-being, with TAM's main variables (e.g., real use, PU, PEU) and PSI—if the technology is visible to others (Kuisma et al., 2007) influencing perceived well-being. Innovativeness is considered as a moderator of the relationships influencing the main TAM variables (Agarwal & Prasad, 1998; Leonard-Barton & Deschamps, 1988; Mittal & Kamakura, 2001). Thus, we position our research in line with other researches that reveal that the adoption of smart technologies is linked to positive

feelings (e.g., Atzori et al., 2010; Etzioni, 1999; Harkin et al., 2016; Kluger & DeNisi, 1996; Porter & Heppelmann, 2014; Xia et al., 2012).

5.1.4. Study of timely concepts

Thus far, consumer well-being has received little attention in marketing research (Hall & Khan, 2002; Lee et al., 2003; Moisio & Beruchashvili, 2010). Therefore, we define and measure the concept of perceived well-being, which is attracting increasing interest of researchers in marketing within the new paradigm of transformative consumer research (TCR) (Anderson et al., 2013; Arora et al., 2017; Kim et al., 2016; Krebs & Duncan, 2015). Created by the Association for Consumer Research, TCR aims to encourage research that benefits and improves consumer well-being during consumption. The main goals of TCR that we attempt to respond to are: improve consumer well-being, encourage paradigm diversity, employ rigorous theory and methods, highlight socio-cultural and situational contexts, identify samples of consumers, and provide valuable results for managers (Mick et al., 2012).

Moreover, social value appears to depend on technology, which is more important when the technology is visible to others (e.g., Kuisma et al., 2007). This is in line with the Triandis theory (1971), which adds a social variable to better understand behaviors toward technology (Milhausen et al., 2006). Finally, privacy concerns are the main obstacles in using the IoT and smart technologies (e.g., Buchanan & Ess, 2006; Hong & Thong, 2013), even if they decrease with experience of use due to benefits of personalization (Dimitriadis & Kyrezis, 2010; Sirdeshmukh et al., 2002) or due to the willingness to give up on privacy issues to experience a new digital experience with IoT and smart technologies (Turow et al., 2008). Nevertheless, little research has focused on privacy concerns in the context of smart devices so far (Fox & Royne, 2018; Verhoef et al., 2017).

5.2. Methodological contributions

Methodological contributions relate to the willingness to increase the internal and external validity of our studies, development of scales, and adaptation to the context of the IoT and smart technologies, as well as the mixed methods employed. These implications are detailed below.

5.2.1. Maximization of internal and external validity

The replication of our studies aims to improve internal validity —do we measure what we want to measure; qualitative and quantitative studies; samples of non-users, innovators, early adopters and the majority of users are surveyed to study learning experiences— (Ashraf et al., 2014; Davis et al., 1989; Gilly et al., 2012; Keil et al., 1995; Rogers, 2003). We also aim to improve external validity with different samples and various IoT and smart technologies —SCO, sleep apps, smart homes, smart stores— (Hasan et al., 2019).

5.2.2. Development of measurement scales

These studies enable the measurement of perceived well-being in the context of the IoT and smart technologies (Bhat et al., 2019). To deepen the measurement of well-being in marketing literature, we consider that well-being has four dimensions: happiness (Munzel et al., 2018), hedonism (Brief & Aldag, 1977; Van der Heijden, 2004; Lowry et al., 2013; Venkatesh et al., 2012), improvement of health (Howie et al., 1998), and quality of life (Diener et al., 1985; Pavot & Diener, 1993, 2008).

Thereby, we use Munzel et al.'s (2018) scale of happiness that we adapt to each context of study. We employ this scale because it considers a cognitive component of individual well-being, affective perception, and overall well-being (Kiefer et al., 2013; Sheldon & Elliot, 1999) and has stable psychometric properties (Munzel et al., 2018). We add items to measure the fun with Brief and Aldag's scale (1977), the health factor with Howie et al.'s scale (1998), and the quality of life with Diener et al.'s scale (1985). Then, we conduct statistical tests to decide to keep or discard certain items in order to obtain the most reliable scale possible. Table 56 presents the initial scales used and the items retained for our studies.

Literature		This thesis		
Scales	Items adapted	Smart objects	Smart apps	Smart environments
Happiness (Munzel et al., 2018)	“iSommeil makes me feel happy.”	Not significant	Significant	Significant
	“In general, I feel better since I use my SCO.”	Significant	Significant	Significant
Fun (Brief & Aldag, 1977)	“I like using my SCO as it is a fun distraction.”	Significant	Not significant	Significant
	“Shopping in smart retail stores would make shopping more entertaining and fun.”	Not significant	Not significant	Significant
	“Smart retail stores would create pleasant distractions and surprises.”	Not significant	Not significant	Significant
Health (Howie et al., 1998)	“iSommeil improves my health and sleep conditions.”	Significant	Significant	Not significant
Quality of life (Diener et al., 1985)	“My SCO improves my quality of life.”	Significant	Significant	Significant

Table 56: Adaptation of the measurement of well-being

Table 56 indicates that according to the technology, a few items are retained or discarded in accordance with reliability indicators. Happiness and quality of life are significant in all IoT contexts of study, whereas the fun dimension is significant only with SCO and smart environments, and the health dimension is significant only in the contexts of SCO and sleep apps. This can be explained by the fact that the health dimension must be more important than the fun dimension for the sleep app, which is more linked to health than entertainments. For the non-significance of the health dimension with smart environments, we hypothesize that people feel that they do not have much control over the influence of smart technologies and over their health since they live in connected environments already submitted to radiations.

We also define and measure traits of personality (i.e., well-being and empowered personalities) (Csíkszentmihályi, 1975; Umans et al., 2016). In order to measure well-being personalities, we use a scale to define people’s temperaments inspired by Hock’s (1962) description of sanguine people (close to the high well-being personality), melancholic people (close to the low well-being personality), phlegmatic people (close to the low empowered personality), and choleric people (close to the high empowered personality). This theory comes from Hippocrates in 460, and has then been re-employed by Kant, or Eysenck (1990) who did factorial analysis with these scales. We were also inspired by Csíkszentmihályi’s (1975) description of autotelic people (close to users with a high well-being personality), and Harris and Westin’s (1991) description of privacy fundamentalists (close to users with a low well-being personality). Initially, the scale comprised 10 items to define each personality, and based on the results of scales reliability, we retain fewer items. Table 57 presents the initial scales, rated from 1 (strongly disagree) to 5 (strongly agree).

High well-being personalities rate higher on the following aspects:	Low well-being personalities rate higher on the following aspects:
I would describe myself as 1. Talkative 2. Full of energy 3. Able to generate a lot of enthusiasm 4. Open to others 5. Curious 6. Often enthusiastic 7. Inspired	I would describe myself as 1. Reserved 2. Somewhat calm 3. Often sad 4. Often tensed 5. Often in a bad mood 6. Easily upset 7. Rather irritable
High-empowered personalities rate higher on the following aspects:	Low-empowered personalities rate higher on the following aspects:
I would describe myself as 1. Affirmed 2. Sociable 3. Managing well stressful situations 4. Self-controlled 5. Rather proud 6. Mentally strong 7. Active	I would describe myself as 1. Shy 2. Erased 3. Often worried 4. Distressed 5. Rather anxious 6. Easily ashamed 7. Rather nervous

Table 57: Final scales of well-being and empowered personalities

We measured high and low personalities in order to make sure that respondents were consistent with their responses. It enables us to discard inconsistent responses for the analysis of the results through SPSS.

5.2.3. Utilization of mixed methods

This thesis combines both qualitative and quantitative studies (Wunderlich et al., 2019): qualitative studies indicate relevant antecedents of the IoT and smart technologies, and quantitative studies measure constructs to deepen research on specific concepts and build theoretical models. Moreover, longitudinal studies on smart apps (before and after usage) improve the understanding of adoption through time and experience of use (Rogers, 2003).

5.3. Managerial contributions

The managerial contributions of this thesis could enable managers to rethink targeting and communication strategies before adoption, along with the key factors of acceptance and usage.

5.3.1. Improve targeting and communication before adoption: key factors of the IoT acceptance

Early adopters first favor and perceive high usefulness and ease-of-use to accept IoT and smart technologies (Calantone et al., 2006; Davis, 1989; Davis et al., 1989; Taylor & Todd, 1995). Therefore, IoT and smart technologies must respond to actual needs by providing an appropriate information at the right time. For example, enabling self-tracking, self-knowledge, and self-management should improve acceptance (Kozinets, 2012). Moreover, the IoT and smart technologies must be simple so that companies can easily advise users on ways to integrate the IoT and smart technologies in daily routines. Therefore, the IoT and smart technologies must offer easy functions with ergonomic and intuitive characteristics (e.g., Calantone et al., 2006; Davis, 1989; Davis et al., 1989; Taylor & Todd, 1995).

Moreover, privacy concerns are the first and main obstacles to adoption and increase consumer reluctance (Bhattacharjee, 2000; Verhoef et al., 2017). Thus, companies must clearly communicate with regard to secondary data usage and security policies in order to increase trust in technology (Shieh et al., 2013). However, even if users are concerned about

privacy issues, they must not stop using the technology if they believe the benefits of personalization are higher than the loss of privacy (Xu et al., 2011). Perceived privacy risks can also be decreased by increasing control and personal knowledge for users through, for example, quantified-self features (e.g., Armitage & Conner, 1999; Awad & Krishnan, 2006; Azjen & Driver, 1991; Fuchs et al., 2010; Kirsch, 1996). Thereby, companies must be transparent with regard to data policies and can focus on social indicators (age, gender, religion), technical parameters (privacy settings, regular safety controls, software, network equipment), and legal solutions (laws and regulations, ethics, moral policies). It must be feasible to educate consumers with regard to health risks, and how to make the technology work in order to reassure them.

5.3.2. Improve product and service features after adoption: key factors of loyalty of use

Then, managers must develop products and services after acceptance through the key factors of adoption, appropriation, and use. Indeed, these utility benefits can be improved through perceived social and well-being benefits, which constitute reasons to continue using the IoT and smart technologies (Andreasen et al., 2012; Bagozzi, 2007; Chitturi et al., 2008; Davis & Pechmann, 2013; Novak et al., 2000; Van der Heijden, 2004; Venkatesh & Davis, 2000). Companies could reward users according to the valuable data shared through the technology networks (the more information provided, the greater rewards, such as discounts, exclusive offers, digital coupons, small gifts, personalized features, or thank you cards). Rewarding consumers could increase their willingness to share private data, improve their satisfaction and well-being, and thus ensure loyalty of use on the long term.

5.3.3. Define segments of IoT users according to smart technologies

This thesis defines and measures different personalities (i.e., well-being and empowered personalities). It is also important to allow companies to define types of IoT users and consumer segments in accordance with smart technologies. The high versus low well-being users and the high versus low empowered users are contrasting types of users, which are attracted to different aspects of technologies. We also show the importance of first targeting innovators and early adopters with rational reasons and utility benefits (Rogers, 2003; Von Hippel, 1986). This differentiation should enable managers to refine marketing strategies according to user-specific needs.

5.3.4. Opportunities for marketing strategies

A huge amount of big data from the IoT networks and sensors can be obtained and analyzed through analytical tools (Lee & Lee, 2015). This can be very useful for management and marketing decisions to create an individual value-added service experience for consumers through real-time event feedback (Lee & Lee, 2015; Remondes & Afonso, 2018). Managers can get real time alerts about their products and services, define and send personalized notifications, analyze the customer journey and profile in store and thus, better define the merchandising strategy. These solutions are mostly based on the nudge economy (i.e., push customers to buy) in order to create a more efficient point of sale and greater profits.

Even though this thesis makes a few contributions, it has certain limitations that must be addressed in order to ensure that the results are employed with caution and to provide room for improvement by indicating future research directions, which are addressed in the next chapter.

CHAPTER 6: GENERAL RESEARCH LIMITS AND FUTURE RESEARCH DIRECTIONS

This thesis aims to target research gaps and deepen the research around the IoT and smart technologies. The studies that are part of this thesis have limitations to be mentioned. Certain limitations of previous studies have already been considered, but there are limitations that are common to all the studies; moreover, general future research directions are presented. In Table 58, we present the limitations of this thesis and future research directions.

Research limits	Research directions
<p>Generalization of the results:</p> <ul style="list-style-type: none"> - Representativeness of the sample: mainly French students from the Y and X generations; results might vary with other cultures and generations (Straub et al., 1997; Hofstede, 2001) - All categories of SCO are considered 	<ul style="list-style-type: none"> - Replicate this study with respondents from all generations as well as from other countries (Straub et al., 1997) and other generations (Bianchi & Andrew, 2012; Colton et al., 2010) - Study the adoption of different SCO according to categories of SCO/environments/smart apps, and for different motivations of use (e.g., mandatory use, hedonic use, useful use, health motivation, work/productiveness motivation, etc.) (Sanzo-Perez et al., 2015)
<p>Methodology:</p> <p><u>Qualitative studies:</u></p> <ul style="list-style-type: none"> - Interpretation can differ according to researchers (Vernette, 2011) - Focus groups: issues regarding confidentiality, anonymity, and potential feelings of being judged by others (Vernette, 2011) 	<ul style="list-style-type: none"> - The methodology could be replicated by other researchers (Vernette, 2011) - Do face-to-face interviews (Vernette, 2011), conduct quantitative studies to build conceptual models (Canhoto & Arp, 2017; Fang et al., 2014)

Research limits	Research directions
<p><u>Quantitative studies:</u></p> <ul style="list-style-type: none"> - No real-time behavior indicators (Ahmadpour et al., 2016) - Our longitudinal study tests the differences in perceptions of a sleep app before and after use only after one week of use whereas intentions and perceptions might change over time (Ashraf et al., 2014; Davis et al., 1989; Keil et al., 1995) 	<ul style="list-style-type: none"> - Collaborate with companies to obtain real-time data (e.g., Ahmadpour et al., 2016; Van Ittersum et al., 2013) - Do more longitudinal studies over a longer period of time, like months or years (Etkin, 2016)
<p>Concepts:</p> <ul style="list-style-type: none"> - Perceived well-being does not take into account objective facts (Diener, 1984) - Measuring perceived well-being with quantitative scales does not take into account all the aspects of this concept - The personalization paradox must be studied in greater detail (Dimitriadis & Kyrezis, 2010) 	<ul style="list-style-type: none"> - Neurotransmitter tests can determine the levels of happy hormones (i.e., serotonin, dopamine, norepinephrine, GABA, etc.) - Further research must use more complex measurement concepts of well-being - Study the extent to which users are ready to share personal information for personalized features or advertising purposes (Dimitriadis & Kyrezis, 2010)
<p>Changing environment:</p> <ul style="list-style-type: none"> - Apparition of new laws, changing demand, media alerts, social influence, and changing beliefs related to the common perceptions of the IoT 	<ul style="list-style-type: none"> - Replicate this study in the coming years to test for differences according to the evolution of technologies, and consumer perceptions

Table 58: Research limits and future research directions of this thesis

Table 58 presents the common limitations of all the studies included in this thesis and future research directions. The main ones are discussed below:

- Generalization of the results: Our sample only represents the X and Y generations from France. Research has shown differences according to cultures and generations (Hofstede, 2001; Straub et al., 1997); thus, the same studies conducted with other nationalities and generations could bring out different results and insights. Moreover, the studies on SCO consider all types of SCO, without a differentiation among them (i.e., smart watch, connected speaker, google home, smart TV, etc.). We did not have sufficient respondents by category of SCO, but if we can differentiate categories of SCO and motivations of use (e.g., hedonic/leisure or utilitarian/work technology), the results could bring out new insights (Sanzo-Perez et al., 2015).

- Methodology: With regard to our qualitative studies, interpretation can differ according to researchers (Verette, 2011); thus, if other researchers conduct the same study employing the same methodology, their interpretation could differ; moreover, they could also decide to use another methodology. Indeed, focus groups create certain limitations due to issues regarding confidentiality and feelings of being judged by others (Verette, 2011). It is also recommended to conduct quantitative studies to build theoretical models (Fang et al., 2014; Canhoto & Arp, 2017), which has been done in our other studies. For our quantitative studies, we could not find real-time behavior indicators (Ahmadpour et al., 2016) because it was difficult to collaborate with companies and the one that collaborated with us did not have access to real-time data yet. Further, longitudinal studies must be conducted over a longer period of time (Ashraf et al., 2014; Davis et al., 1989; Keil et al., 1995). We would like to reproduce these studies with longitudinal studies over a longer period —over months or years— to obtain additional or different insights (Etkin, 2016).

- Concepts: Perceived well-being must also take into account objective facts (Diener, 1984). It is difficult to measure well-being because it can depend on numerous other indicators (i.e., moods, good/bad news received, health issues, etc.). Elaborating an experience with neurotransmitter tests could be another way to measure levels of well-being and push forward research on well-being, even though this requires significant financial resources. Moreover, the personalization paradox must be studied in detail (Dimitriadis & Kyrezis, 2010). We could study the extent to which users are ready to share their personal information in order to obtain personalized features or advertising purposes (Dimitriadis & Kyrezis, 2010). Indeed, people

must be more willing to provide personal information when they can obtain a personalized benefit from this action (Hong & Thong, 2013; Xu et al., 2011); thus, it could be interesting to relate benefits to degrees of privacy.

- Changing environment: The IoT environment evolves with new laws, changing demand and behaviors, media alerts, and social influence, thereby changing beliefs about the image of the IoT. Therefore, these results could differ in the coming years with the evolution of the industrial market and consumer environments, thus changing consumer perceptions and behaviors.

Conclusion to Part III

Part III sums up the discussions, contributions, and research limits of all our studies. The acceptance of the IoT and smart technologies is strengthened by utility benefits —namely PU and PEU— then adoption and usage are favored by perceived well-being and social benefits. The main reticence linked to privacy concerns can be compensated with a higher utility value or social value. Moreover, perceived well-being can decrease with usage due to the perceived addiction effects or the lack of perceived benefits.

The first contribution of this research is to clarify the concept of the IoT and its components. We suggest that *“the IoT is a network of networks which includes smart/connected objects, mobile applications and collected data stocked in data platforms to improve user targeting, and personalization features for better consumer experience and quality of life”* (Attié & Meyer-Waarden, 2018).

The second main contribution is the understanding of the acceptance and adoption processes of the IoT and smart technologies through our willingness to improve internal and external validity and, thus, the choice to employ a mixed methods approach.

The third main contribution is the understanding of the consequences of IoT and smart technologies on perceived well-being.

The main limits of our research are related to the generalization of the results due to the sample and the small period of the longitudinal study. Besides, measuring perceived well-being with quantitative scales does not take into account all the aspects of this concept and this must be further addressed in future research.

GENERAL CONCLUSION

Over the previous decade, researchers have been interested in the concept of the IoT and smart technologies (Verhoef et al., 2017). It has often been complicated to decide whether to include smartphones into this category. A smartphone is a smart technology and should be included in the concept of the IoT, but it is not perceived as an innovation anymore. We thus define the IoT as a network of networks, which includes smart/connected objects, mobile applications and collected data stocked in data platforms to improve user targeting, and personalization features for better consumer experience and quality of life.

The literature on technology acceptance is extensive and, thus, we decided to begin our research with a qualitative study on IoT contexts, such as smart connected objects, smart apps, smart homes, and smart stores. This preliminary study discussed the following antecedents of the acceptance of the IoT and smart technologies —perceived usefulness, perceived ease of use, perceived well-being, perceived social image, privacy concerns, quantified-self, and different personalities—. Based on a literature review, we built theoretical models to better understand the roles of each variable. In order to increase the validity of these findings, we conducted replications with four quantitative studies in four different contexts: smart connected objects, sleep apps, smart homes, and smart stores. It appears that theoretical models should adapt to the technology and IoT contexts of study.

Further, the consequences of the IoT and smart technologies on perceived well-being need to be more deeply studied (Etkin, 2016). According to the validity of our samples, we decided to study the directions of the relationship between adoption and perceived well-being, as this is not clear in the literature (Munzel et al., 2018; Steptoe et al., 2012). Therefore, it became evident that technology, actual use, utility benefits, and social benefits have a positive or negative influence on perceived well-being in accordance with experience of use and personalities.

In the future, we predict a growing academic and managerial interest in the IoT and smart technologies, as the domain is increasingly being developed by companies and adopted by consumers. These technologies must function to improve quality of life (Porter & Heppelmann, 2014), and it is important to ensure that companies' profits are in line with ensuring that consumers' security and well-being needs are met. We hope that this thesis provides insights to both academic and managerial researchers and continues to pave the way for additional future research on this topic.

APPENDICES

Appendix 1: Literature review

Appendix 1A: Literature review

Publication; Methodology	Antecedents of acceptance	Limits and research gaps
<p>Understanding the factors affecting the adoption of the Internet of Things (Hsu & Yeh, 2017)</p> <p>Methodology:</p> <ul style="list-style-type: none"> - Model combined from the TOE (Technology-Organization-Environment; Tornatzky & Fleischer, 1990) and DEMATEL (Decision-making Trial and Evaluation Laboratory; Geneva Research Centre of the Battelle Memorial Institute, 1972) 	<ul style="list-style-type: none"> - Environment - Organization - Security 	<ul style="list-style-type: none"> - Other methods could be used, such as interviews or case studies to identify new constructs (Hsu & Yeh, 2017)
<p>A study on the adoption of IoT smart home service: using value based adoption model (Kim et al., 2017)</p> <p>Methodology:</p> <ul style="list-style-type: none"> - Model combining value-based adoption model (VAM) (Kim et al., 2007), technology acceptance model (TAM) (Davis et al., 1989), unified theory of acceptance 	<ul style="list-style-type: none"> - Perceived benefit: usefulness (degree of improved performance after use; Davis, 1989), enjoyment (degree of pleasure felt with use; Agarwal & Karahanna, 2000), facilitating conditions (degree of belief in the organizational and technical infrastructure supported for use; Davis, 1989) - Perceived sacrifice: technicality (degree of difficulty in usage; 	<ul style="list-style-type: none"> - The IoT service is explained to respondents with a video and could, thus, cause biases of interpretation (Kim et al., 2017) - There is a small number of samples, so the explanatory power of variables is limited to a certain extent (Kim et

Publication; Methodology	Antecedents of acceptance	Limits and research gaps
<p>and use of technology (UTAUT) (Venkatesh et al., 2003), and elaboration likelihood model (ELM) (Petty & Cacioppo, 1986)</p> <p>- Quantitative study (N = 269)</p>	<p>Davis, 1989), perceived fee (perception regarding fee), privacy risk (concern for the management of information and privacy), innovation resistance (negative attitude regarding changes from adoption)</p> <p>- Moderator: variety seeking (inclination to explore various services)</p>	<p>al., 2017)</p>
<p>Exploring the factors that support adoption and sustained use of health and fitness wearables (Canhoto & Arp, 2017)</p> <p>Methodology:</p> <p>- Exploratory approach guided by theory (N = 20; focus groups; Germany)</p>	<p>- Technology: functional features, access to the data, look and size, willingness to pay</p> <p>- Context: social influence, Receiving financial incentives from employers and insurance providers</p> <p>- User characteristics with perceived affinity to technology</p>	<p>- Use a broader sample of users in other countries and with other generations (Canhoto & Arp, 2017)</p> <p>- A longitudinal quantitative study could highlight new antecedents (Canhoto & Arp, 2017)</p>
<p>Drivers of consumers' resistance to smart products (Mani & Chouk, 2017)</p> <p>Methodology:</p> <p>- Quantitative study with structural equation modelling to test the conceptual model (N = 402)</p>	<p>User resistance is influenced by:</p> <p>- Product characteristics, with perceived usefulness, price (degree of appropriate monetary sacrifice; Zeithaml, 1988), novelty (the extent to which it is unique, different, recent or new; Mani & Chouk, 2017), visual aesthetics</p> <p>- User characteristics, with privacy concerns, intrusiveness (degree to which it enters into</p>	<p>- Reproduce this study with countries other than France and with smart products other than smartwatches in order to identify new antecedents (Mani & Chouk, 2017)</p>

Publication; Methodology	Antecedents of acceptance	Limits and research gaps
	users' lives without permission; Mani & Chouk, 2017), dependence (degree of reliance upon technology; Park et al., 2014), self-efficacy (perceived ability to use the technology; Compeau & Higgins, 1995)	
<p>Adoption of sustainable technologies: a mixed-methods study of German household (Wunderlich et al., 2019)</p> <p>Methodology:</p> <ul style="list-style-type: none"> - Mixed-methods design: literature review, qualitative study (N = 24; inductive method) and quantitative study (N = 930; email surveys) 	<ul style="list-style-type: none"> - Motivation: attitude (affective or evaluative judgment; Fishbein & Ajzen, 1975), internal perceived locus of control (PLOC; reasons for a behavior attributed to self; Malhotra et al., 2008), external PLOC (reasons for a behavior attributed to external agreement; Malhotra et al., 2008), introjected PLOC (misalignment of perceived social influences and personal values; Malhotra et al., 2008) - Household demographic: age, education, income, size - Electricity consumption: electricity consumption and costs, switching electricity providers - Perceived privacy risk (potential loss of control over personal information; Featherman & Pavlou, 2003) - Innovation: innovativeness, willingness to pay 	<ul style="list-style-type: none"> - Study conducted in Germany to be reproduced in other countries (Wunderlich et al., 2019) - Longitudinal studies are recommended (Brown & Venkatesh, 2005; Wunderlich et al., 2019)

Table 59: Main articles on the adoption of the IoT and smart technologies

Appendix 1B: Main theories of technology acceptance

Rogers, 1962 (Innovation Diffusion Theory—IDT)

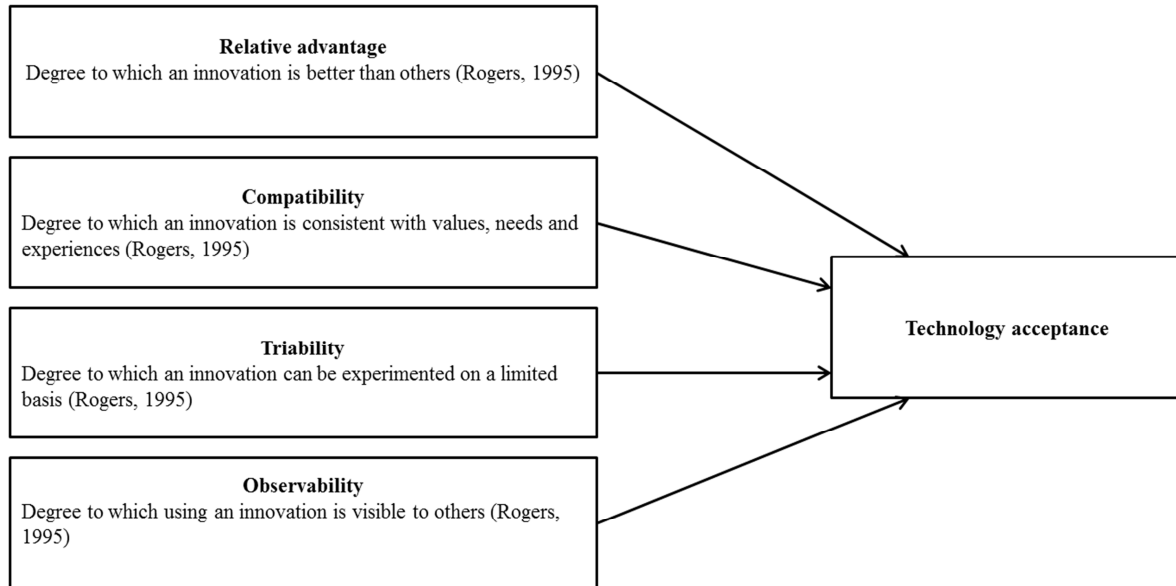


Figure 44: Innovation Diffusion Theory (Rogers, 1962)

Theory and methodology	Main advantages	Main limits
<p>Rogers, 1962 (The Innovation Diffusion Theory—IDT)</p> <p>Study: 508 diffusion research studies</p> <p>Technology: Technology, learning, social structure</p> <p>Definition: The IDT explains the adoption of new technologies adoption according to theory</p>	<p>- The IDT is successfully used in various fields (communication, agriculture, social work, marketing, education)</p>	<p>- The IDT works better for explaining adoption than rejection (Rogers, 1962)</p> <p>- The IDT lacks certain variables like individual characteristics (Rogers, 1962)</p>

Table 60: Innovation Diffusion Theory (Rogers, 1962)

Fishbein, 1967 (Theory of Reasoned Action—TRA)

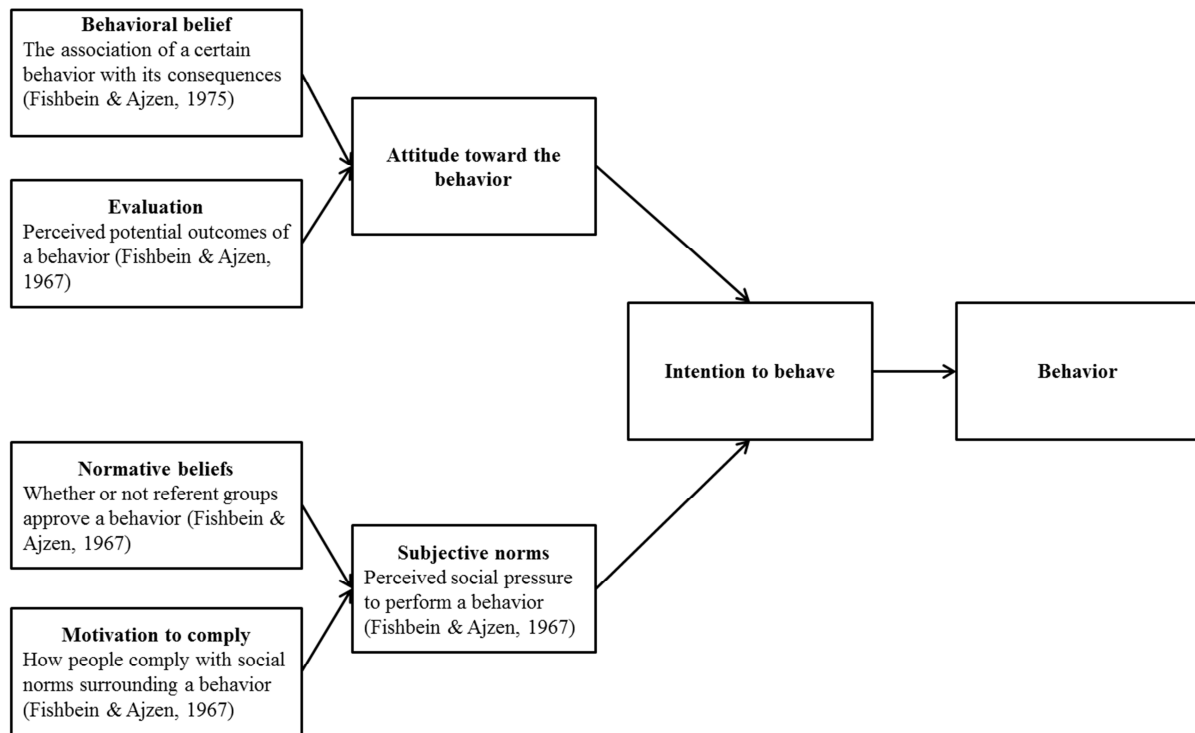


Figure 45: Theory of Reasoned Action (Fishbein, 1967)

Theory and methodology	Main advantages	Main limits
<p>Fishbein, 1967 (The Theory of Reasoned Action—TRA) Study: 109 studies Sector: Health Definition: The TRA shows what variables influence intentions to behave</p>	<p>- The TRA can be applied to various contexts (Fishbein & Ajzen, 1975)</p>	<p>- The TRA is not falsifiable (Ogden, 2003) - Affective and cognitive components must be differentiated (Ajzen & Fishbein, 2005; Triandis, 1980; Triandis, 1980)</p>

Table 61: Theory of Reasoned Action (Fishbein, 1967)

Triandis, 1971 (Theory of Interpersonal Behavior—TIB)

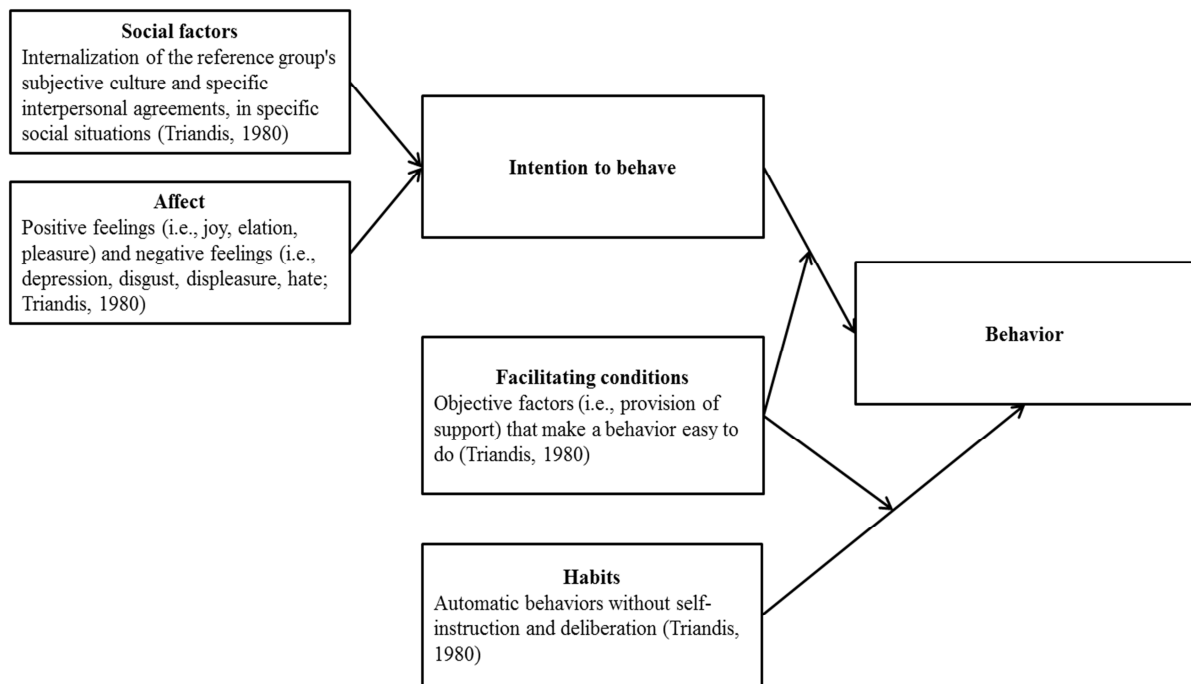


Figure 46: Theory of Interpersonal Behavior (Triandis, 1971)

Theory and methodology	Main advantages	Main limits
<p>Triandis, 1971 (The Theory of Interpersonal Behavior—TIB) Sector: Health Definition: The TIB allows to better understand behaviors toward technology (Milhausen et al., 2006)</p>	<ul style="list-style-type: none"> - Emotional antecedents have received research support (Bagozzi et al., 2002) - The TIB adds an explanatory value (Milhausen et al., 2006) - The TIB can be applied to numerous contexts (Milhausen et al., 2006) 	<ul style="list-style-type: none"> - The TIB contains more constructs than other models, such as the TRA or TPB (Triandis, 1980) - Other antecedents must be studied as well (Thompson et al., 1991)

Table 62: Theory of Interpersonal Behavior (Triandis, 1971)

Ajzen, 1985 (Theory of Planned Behavior—TPB)

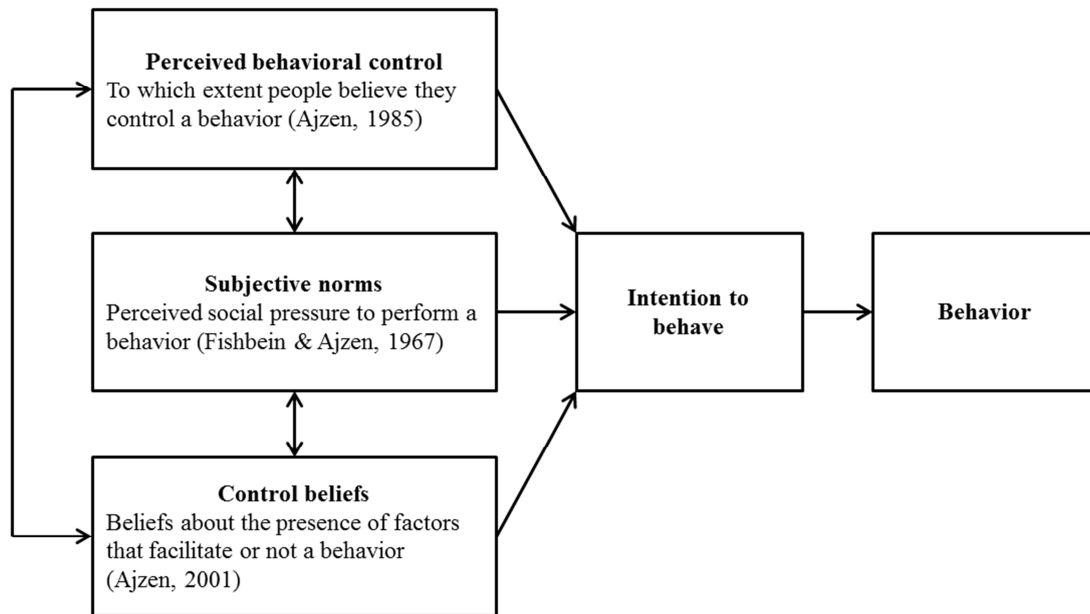


Figure 47: Theory of Planned Behavior (Ajzen, 1985)

Theory and methodology	Main advantages	Main limits
<p>Ajzen, 1985 (Theory of Planned Behavior—TPB)</p> <p>Study: N of 25–30 is the minimum recommended (Ajzen, 1985)</p> <p>Sector: Health</p> <p>Definition: The TPB links people’s beliefs and behaviors (Ajzen, 1985)</p>	<ul style="list-style-type: none"> - The TPB covers people’s unintentional behavior (Ajzen, 1985) - The TPB can be applied to various contexts (Courneya et al., 2000) 	<ul style="list-style-type: none"> - The TPB shows a lack of external validity (Sniehotta, 2009) - Emotions are not considered (Sniehotta, 2009) - The TPB does not explain usage intentions (Davis et al., 1989; Mathieson, 1991)

Table 63: Theory of Planned Behavior (Ajzen, 1985)

Davis, 1986 (Technology Acceptance Model—TAM)

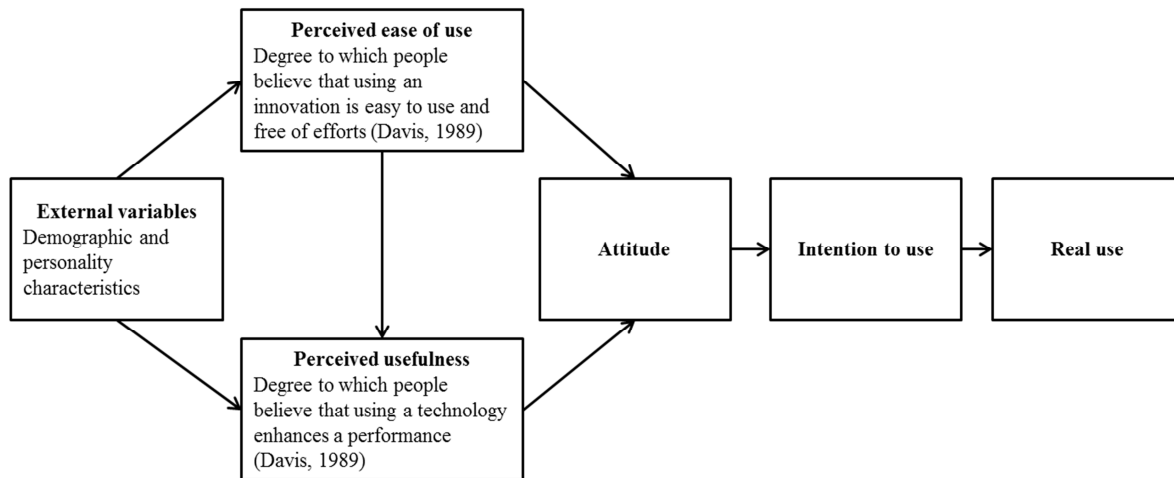


Figure 48: Technology Acceptance Model (Davis, 1986)

Theory and methodology	Main advantages	Main limits
<p>Davis, 1986 (Technology Acceptance Model—TAM)</p> <p>Study 1: N = 112 (Canada)</p> <p>Study 2: N = 40 (England)</p> <p>Technology: 4 app programs</p> <p>Definition: The TAM explains the manner in which users accept and use a technology (Davis, 1986)</p>	<ul style="list-style-type: none"> - The TAM is the most influential theory for predicting attitudes toward technology (King & He, 2006; Venkatesh et al., 2003) - Scales are valid and reliable (Hendrickson et al., 1993) - The TAM is a robust model with strong psychometric properties (King & He, 2006; Lederer et al., 2000; Legris et al., 2003) 	<ul style="list-style-type: none"> - The TAM has a limited predictive power, and a lack of practical value (Chuttur, 2009) - Other variables should be studied (Bagozzi, 2007) - The TAM is not adapted for new technologies (Benbasat & Barki, 2007) - PEU is not always significant (Hu et al., 1999; Wu & Wang, 2005)

Table 64: Technology Acceptance Model (Davis, 1986)

Bandura, 1986 (Social Cognitive Theory—SCT)

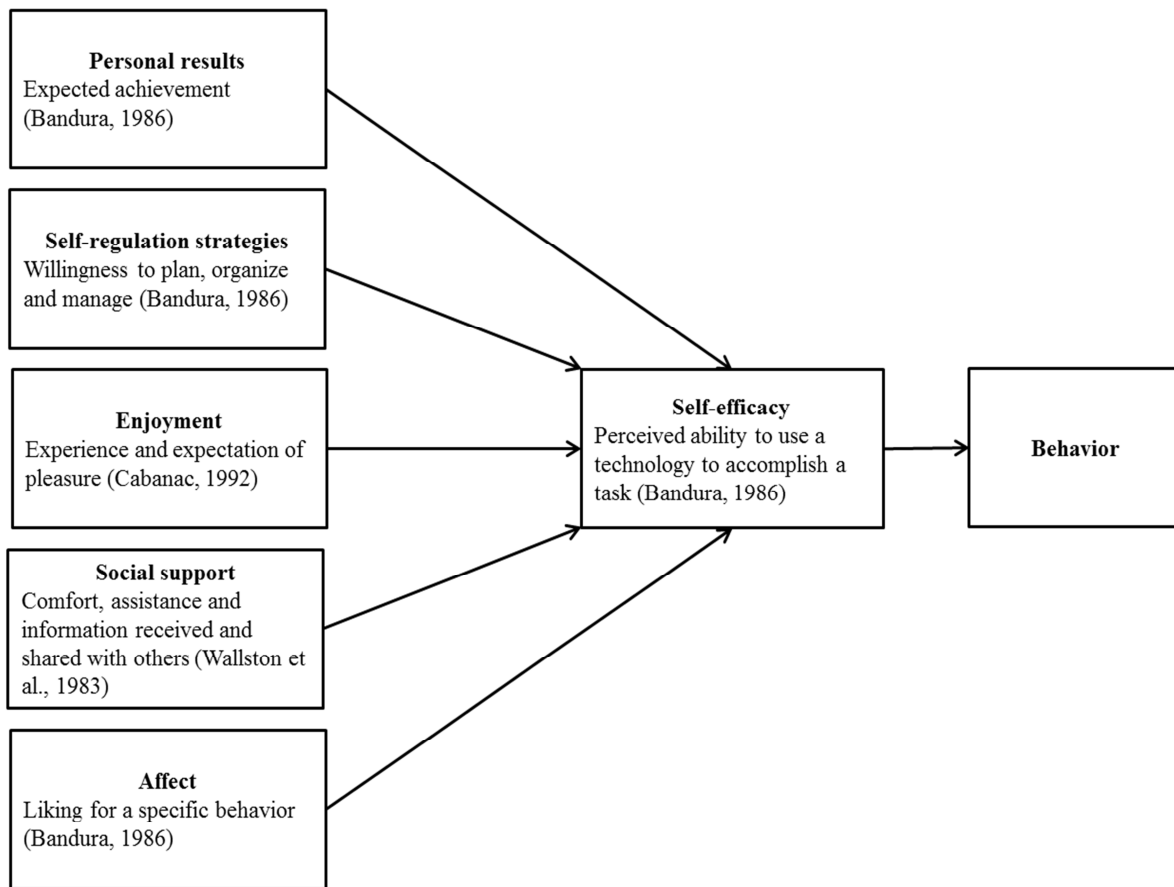


Figure 49: Social Cognitive Theory (Bandura, 1986)

Theory and methodology	Main advantages	Main limits
<p>Bandura, 1986 (The Social Cognitive Theory—SCT) Study: N = 132 (students, Israel) Technology: Learning programs Definition: The SCT posits that people learn from one another, behaviors are goal directed, and that users are self-reflective and capable of self-regulation (Bandura, 1986)</p>	<p>- The SCT can be applied to various contexts (Bandura, 1986)</p>	<p>- The SCT focuses more on environments than on emotions and personalities (Myers, 2010)</p>

Table 65: Social Cognitive Theory (Bandura, 1986)

Scherer, 1986 (Matching Person and Technology Model—MPTM)

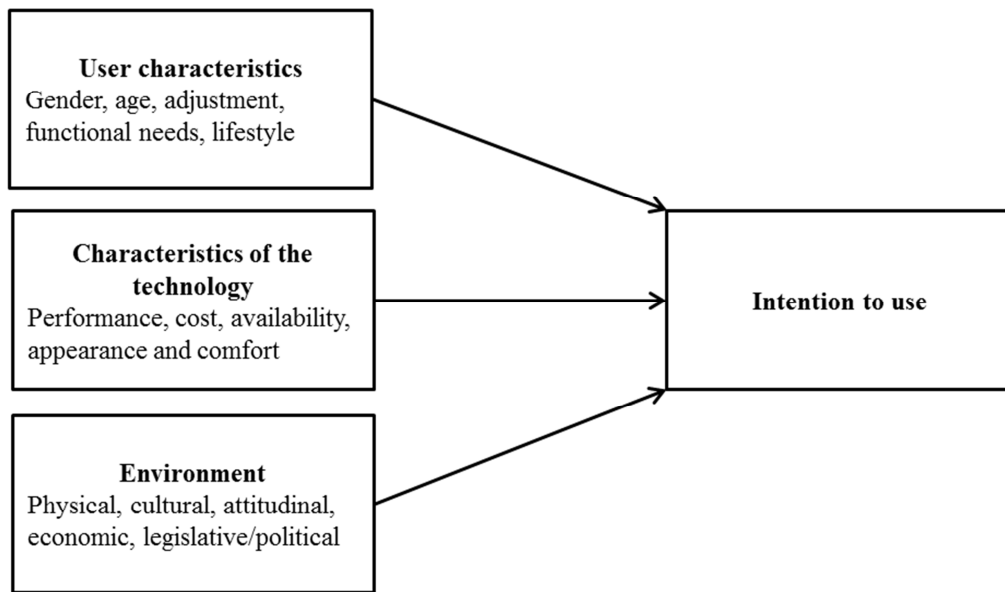


Figure 50: Matching Person and Technology Model (Scherer, 1986)

Theory and methodology	Main advantages	Main limits
<p>Scherer, 1986 (The Matching Person and Technology Model—MPTM) Study: N = 177 (128 users, 49 non-users with disabilities; professionals and students; US and Canada) Sector: Health Definition: The MPTM matches people with the most appropriate technology</p>	<ul style="list-style-type: none"> - Constructs are reliable, scales are valid, and there is an internal consistency (Scherer, 1986) - The MPTM enables the comparison of technologies (Scherer & Craddock, 2002) 	<ul style="list-style-type: none"> - The MPTM is adapted to the healthcare sector and to the US/Canadian market (Scherer & Craddock, 2002)

Table 66: Matching Person and Technology Model (Scherer, 1986)

Moore & Benbasat, 1991 (Instrument to measure the perceptions of adopting an information technology innovation)

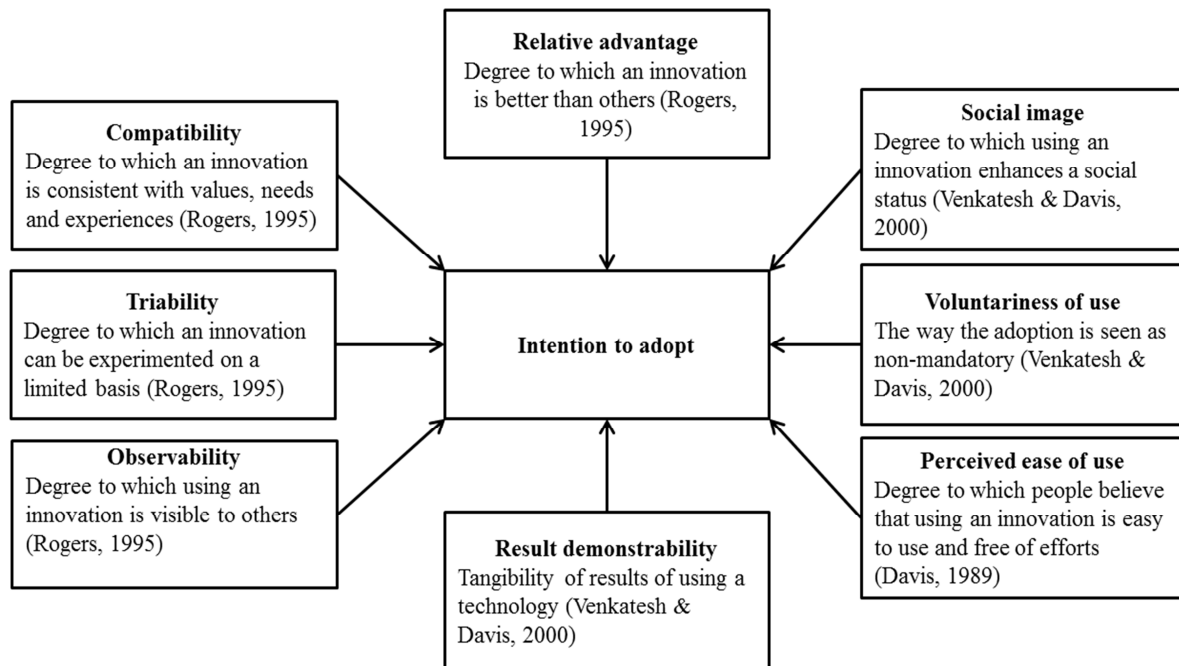


Figure 51: Instrument to measure the perceptions of adopting an information technology innovation (Moore & Benbasat, 1991)

Theory and methodology	Main advantages	Main limits
<p>Moore & Benbasat, 1991 (Instrument to measure the perceptions of adopting an innovation)</p> <p>Study: N = 540 (7 companies)</p> <p>Technology: Innovations</p> <p>Definition: This theory develops an instrument to measure perceptions that people may have of adopting an information innovation</p>	<p>- A 34-item instrument and seven scales with acceptable levels of reliability (Moore & Benbasat, 1991)</p>	<p>- Study based on a specific innovation (personal work station), in a specific context (organizational work) so other contexts may introduce new antecedents (Moore & Benbasat, 1991)</p>

Table 67: Instrument to measure the perceptions of adopting an information technology innovation (Moore & Benbasat, 1991)

Thompson et al., 1991 (PC Utilization Model—PCUM)

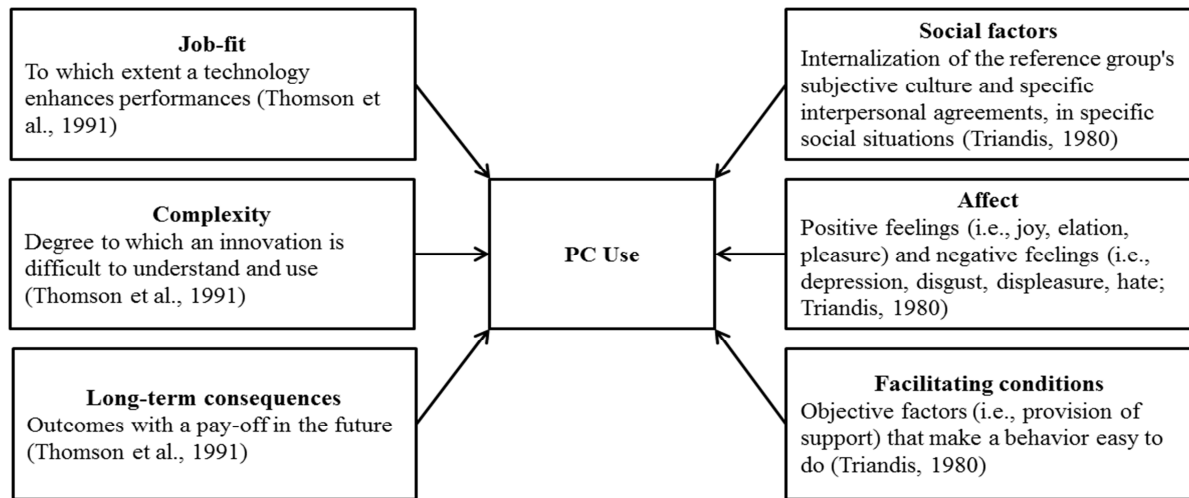


Figure 52: PC Utilization Model (Thompson et al., 1991)

Theory and methodology	Main advantages	Main limits
<p>Thompson et al., 1991 (The PC Utilization Model—PCUM)</p> <p>Study: N = 212 (a multi-national firm)</p> <p>Technology: Personal computer</p> <p>Definition: The PCUM extends the TIB with a distinction between cognitive and affective components of attitudes (Thompson et al., 1991)</p>	<p>- The PCUM is supported in various researches (Davis et al, 1989)</p>	<p>- Differences may occur according to the context of study (Thomson et al., 1991)</p> <p>- Sample from one organization, thereby making it difficult to generalize the results (Thomson et al., 1991)</p> <p>- The measure of affect does not measure all its facets (Thomson et al., 1991)</p>

Table 68: PC Utilization Model (Thompson et al., 1991)

Davis et al., 1992 (Motivation Model—MM)

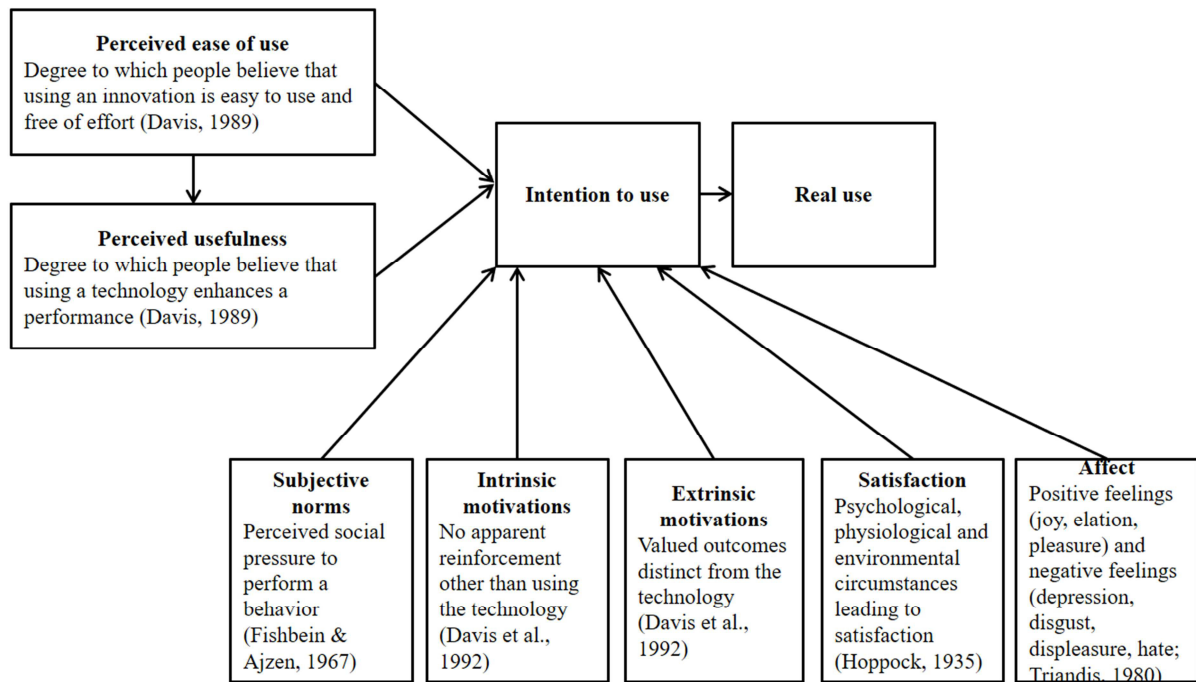


Figure 53: Motivation Model (Davis et al., 1992)

Theory and methodology	Main advantages	Main limits
<p>Davis et al., 1992 (The Motivation Model—MM)</p> <p>Study 1: Word processing software</p> <p>Study 2: Business graphics programs</p> <p>Definition: The MM suggests that behaviors toward technology are based on extrinsic and intrinsic motivations</p>	<ul style="list-style-type: none"> - The MM differentiates between extrinsic and intrinsic motivations (Davis et al., 1992) - External validity is enhanced by two studies (Davis et al., 1992) 	<ul style="list-style-type: none"> - The impact of enjoyment with PU and usage intentions must be examined more deeply (Davis et al., 1992)

Table 69: Motivation Model (Davis et al., 1992)

Taylor & Todd, 1995 (Combined TAM-TPB)

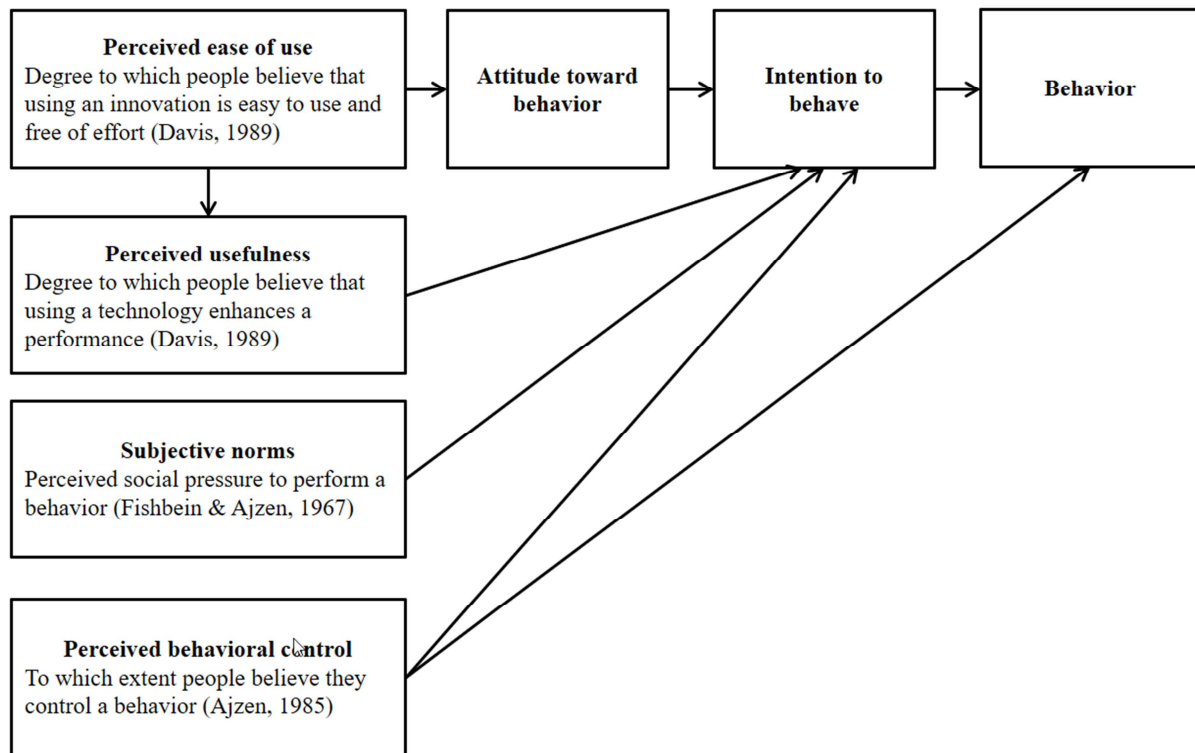


Figure 54: Combined TAM-TPB (Taylor & Todd, 1995)

Theory and methodology	Main advantages	Main limits
<p>Taylor & Todd, 1995 (Combined TAM-TPB)</p> <p>Study: N = 786 (58% users, 42% non-users; two-times study)</p> <p>Technology: Computer resource center</p> <p>Definition: Combined TAM-TPB explains the usage of information technology, using the TAM and TPB</p>	<ul style="list-style-type: none"> - A large sample size, a repeated study (two times), and a realistic setting to strengthen the theory (Taylor & Todd, 1995) - Measures of each construct based on validated scales (Taylor & Todd, 1995) - It adds some value to the TAM and TPB taken separately (Mathieson, 1991) 	<ul style="list-style-type: none"> - The TAM is preferable to study technology usage (Taylor & Todd, 1995) - An issue of self-generated validity (Feldman & Lynch, 1988) - Subjective norms, efficacy, and facilitating conditions do not increase the predictive power of the model (Taylor & Todd, 1995)

Table 70: Combined TAM-TPB (Taylor & Todd, 1995)

Venkatesh & Davis, 2000 (Technology Acceptance Model 2—TAM 2)

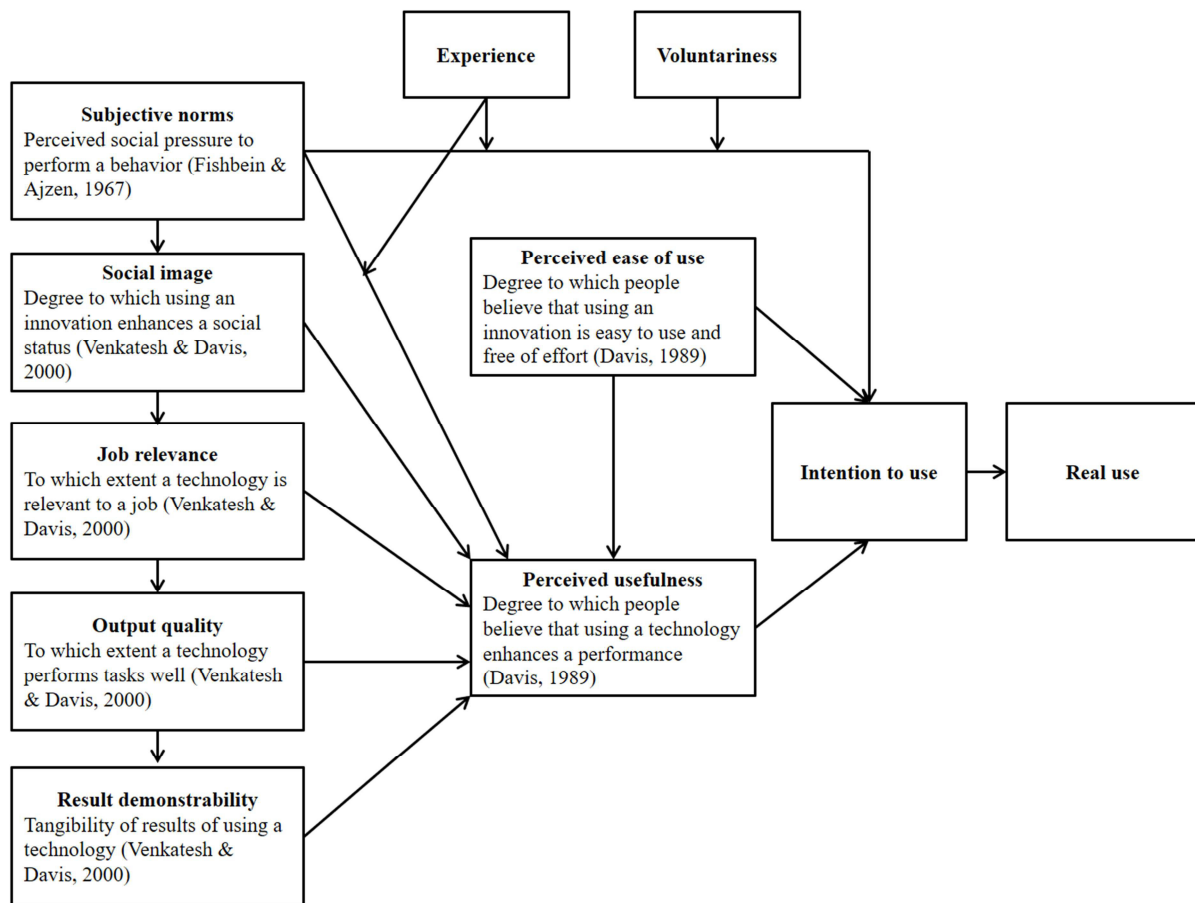


Figure 55: Technology Acceptance Model 2 (Venkatesh & Davis, 2000)

Theory and methodology	Main advantages	Main limits
<p>Venkatesh & Davis, 2000 (Technology Acceptance Model 2—TAM 2)</p> <p>Study: N =156 (4 US organizations; 3-times study)</p> <p>Technology: 4 systems</p> <p>Definition: The TAM 2 provides a better understanding of PU and usage motivations by adding social influence and cognitive processes to the TAM</p>	<ul style="list-style-type: none"> - The TAM 2 shows the important roles of social influence (Venkatesh & Davis, 2000) - PEU becomes less significant over time, due to experience of use (Venkatesh & Davis, 2000) 	<ul style="list-style-type: none"> - Some constructs are measured with two items (i.e., intention to use, subjective norms, job relevance, output quality; Venkatesh & Davis, 2000) - No structural equation modelling (Venkatesh & Davis, 2000)

Table 71: Technology Acceptance Model 2 (Venkatesh & Davis, 2000)

Parasuraman, 2000 (Technology Readiness Index—TRI)

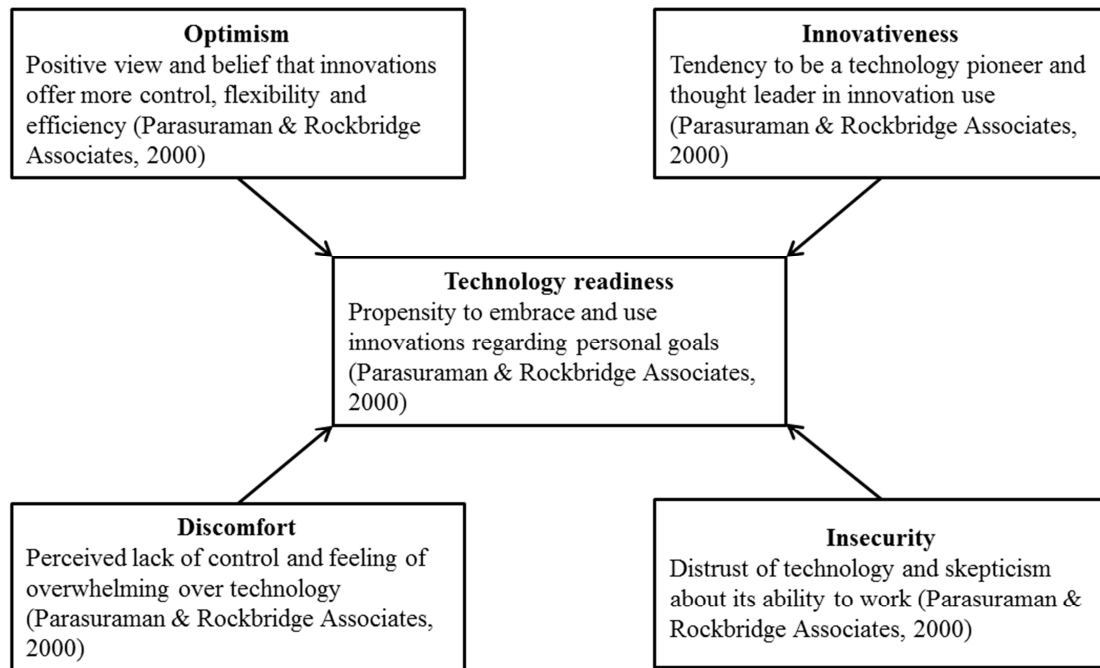


Figure 56: Technology Readiness Index (Parasuraman, 2000)

Theory and methodology	Main advantages	Main limits
<p>Parasuraman, 2000 (Technology Readiness Index—TRI)</p> <p>Study 1: N = 237 (China; paper survey)</p> <p>Study 2: N = 231 (US; online survey)</p> <p>Technology: Innovations</p> <p>Definition: The TRI is a multiple-item scale that evaluates consumers' readiness to interact and use innovations</p>	<p>- The TRI is a cross-culturally valid instrument that can be used in various countries (Parasuraman, 2000)</p>	<p>- The TRI has too many items for empirical studies (Liljander et al., 2006)</p> <p>- The TRI has low model fit indices (Parasuraman, 2000)</p> <p>- Other countries than the US and China must be surveyed too (Parasuraman, 2000)</p>

Table 72: Technology Readiness Index (Parasuraman, 2000)

Venkatesh et al., 2003 (Unified Theory of Acceptance and Use of Technology 1—UTAUT1)

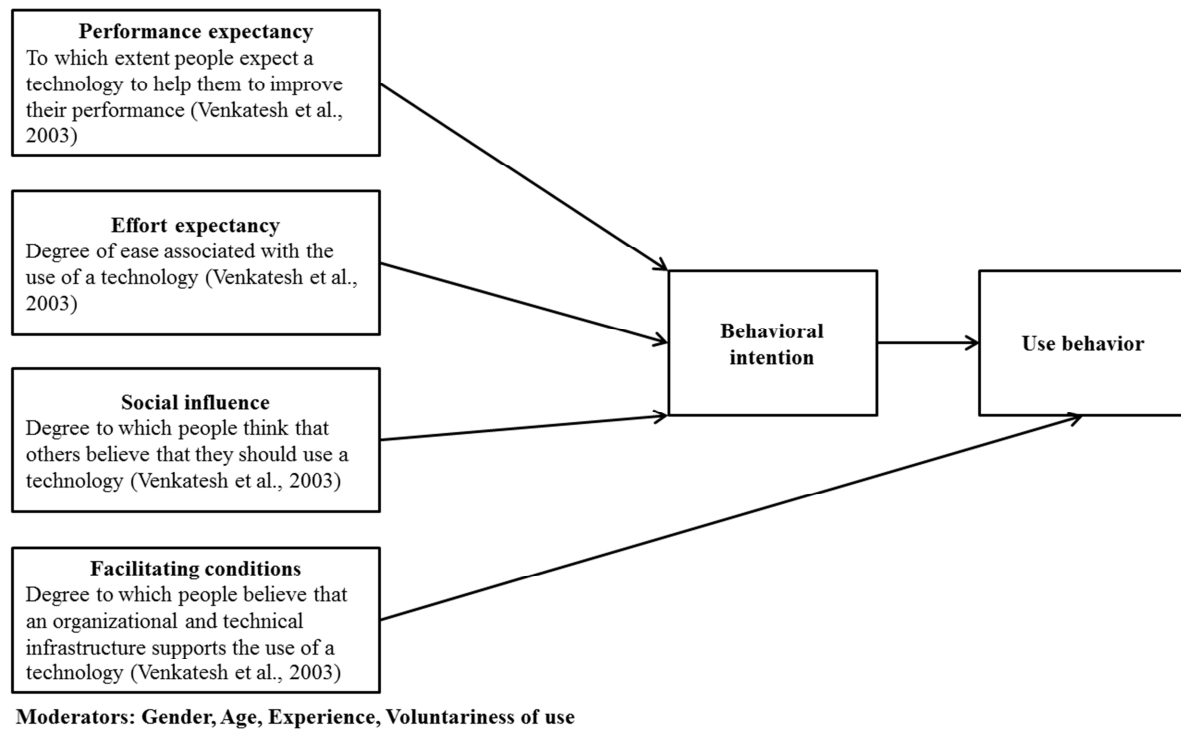


Figure 57: Unified Theory of Acceptance and Use of Technology 1 (Venkatesh et al., 2003)

Theory and methodology	Main advantages	Main limits
<p>Venkatesh et al., 2003 (Unified Theory of Acceptance and Use of Technology 1—UTAUT1) Study 1: N = 54; Study 2: N= 65; Study 3: N= 58; Study 4: N= 38 Technology: 1: online meetings (voluntary) 2: database application (voluntary) 3: portfolio analyzer (mandatory) 4: proprietary accounting systems (mandatory) Definition: The UTAUT evaluates the degree to which people have the intention to use a technology</p>	<p>- The UAUT has been supported in various contexts (El-Gayar & Moran, 2006)</p>	<p>- The UTAUT is very complex with more than 41 independent variables for predicting intentions (Bagozzi, 2007) - Emotions and hedonism must be studied too (Venkatesh et al., 2012)</p>

Table 73: Unified Theory of Acceptance and Use of Technology 1 (Venkatesh et al., 2003)

Curran & Meuter, 2005 (Attitude of Intention to Use Model—AIM)

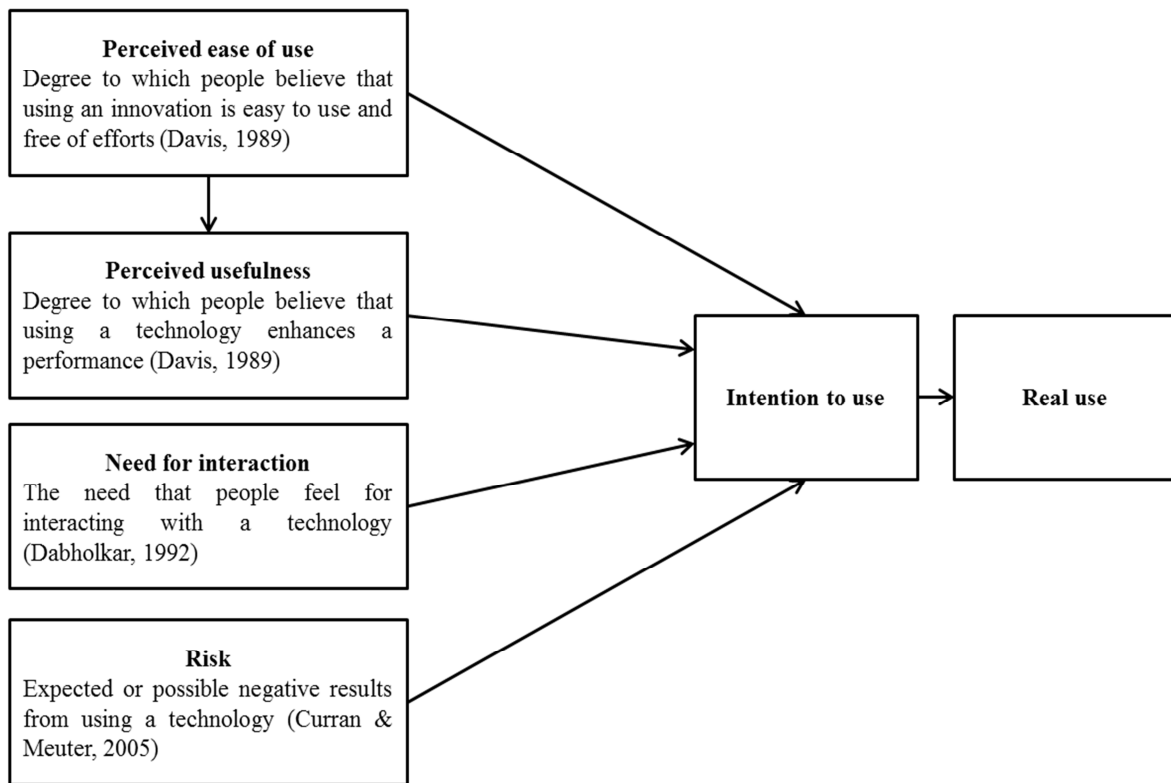


Figure 58: Attitude of Intention to Use Model (Curran & Meuter, 2005)

Theory and methodology	Main advantages	Main limits
<p>Curran & Meuter, 2005 (The Attitude of Intention to Use Model—AIM)</p> <p>Technology: Online banking</p> <p>Definition: The AIM allows a better understanding of consumer decision toward a technology</p>	<p>- The AIM brings out new insights with new factors (risk and need for interaction) (Curran & Meuter, 2005)</p>	<p>- The AIM is only significant in banking contexts and offers low empirical support (Curran & Meuter, 2005)</p>

Table 74: Attitude of Intention to Use Model (Curran & Meuter, 2005)

Venkatesh & Bala, 2008 (Technology Acceptance Model 3—TAM 3)

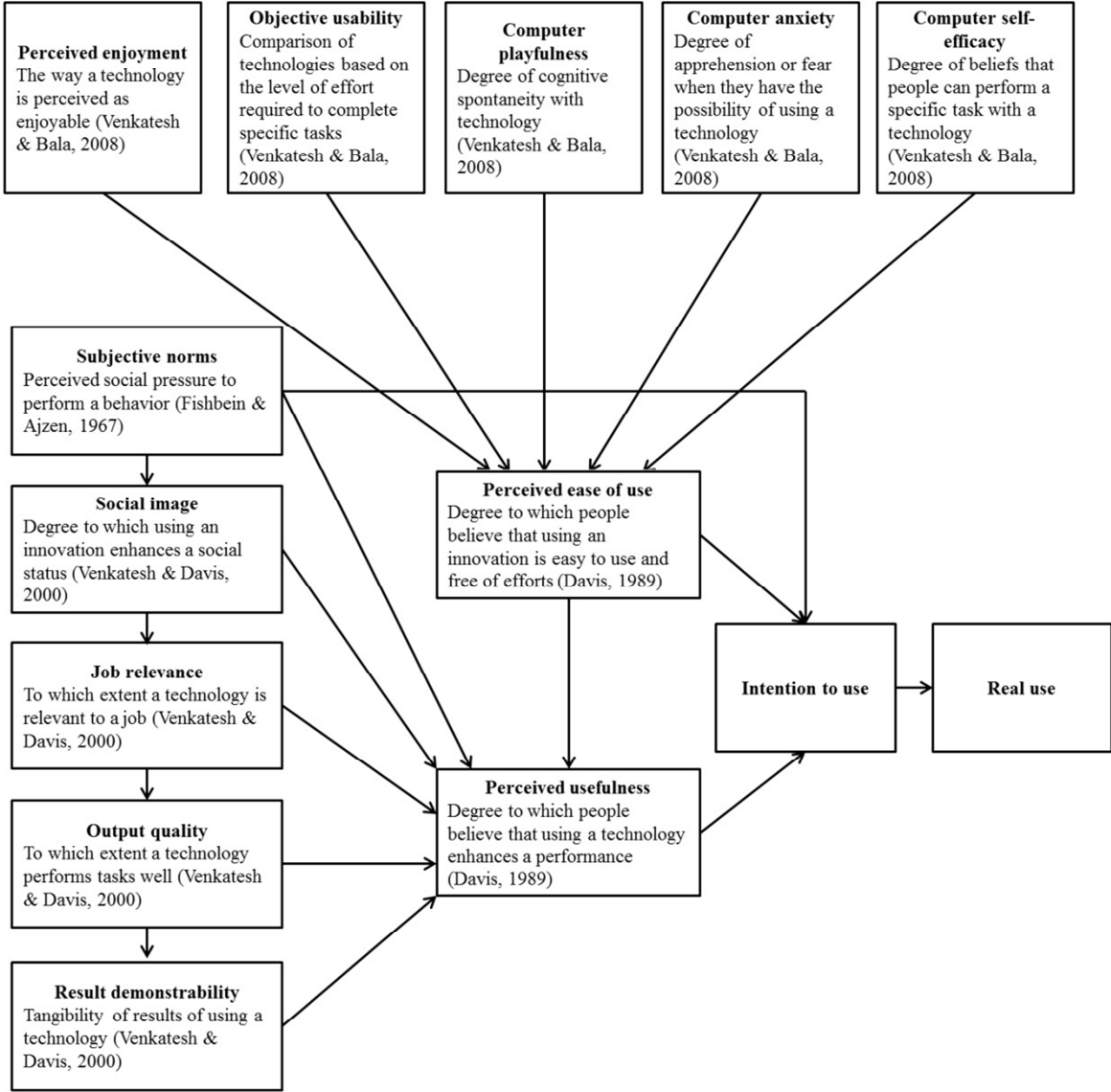


Figure 59: Technology Acceptance Model 3 (Venkatesh & Bala, 2008)

Theory and methodology	Main advantages	Main limits
<p>Venkatesh & Bala, 2008 (Technology Acceptance Model 3—TAM 3) Study: N = 468 Technology: Information technologies in the workplace Definition: The TAM 3 adds additional factors to the TAM 2 to better understand PEU</p>	<ul style="list-style-type: none"> - The TAM 3 explains the antecedents of PEU which is an important antecedent of technology adoption (Venkatesh & Bala, 2008) - The TAM 3 takes into account the concept of perceived enjoyment (Benbasat & Barki, 2007) 	<ul style="list-style-type: none"> - Lack of theoretical validations (Venkatesh & Bala, 2008) - Mixed results regarding social influences (Venkatesh & Bala, 2008) - The TAM 3 considers a binary behavior (acceptance or rejection), putting research away from the evolution of acceptance over time

Table 75: Technology Acceptance Model 3 (Venkatesh & Bala, 2008)

Beaudry & Pinsonneault, 2010 (Coping Model of User Adaptation—CMUA)

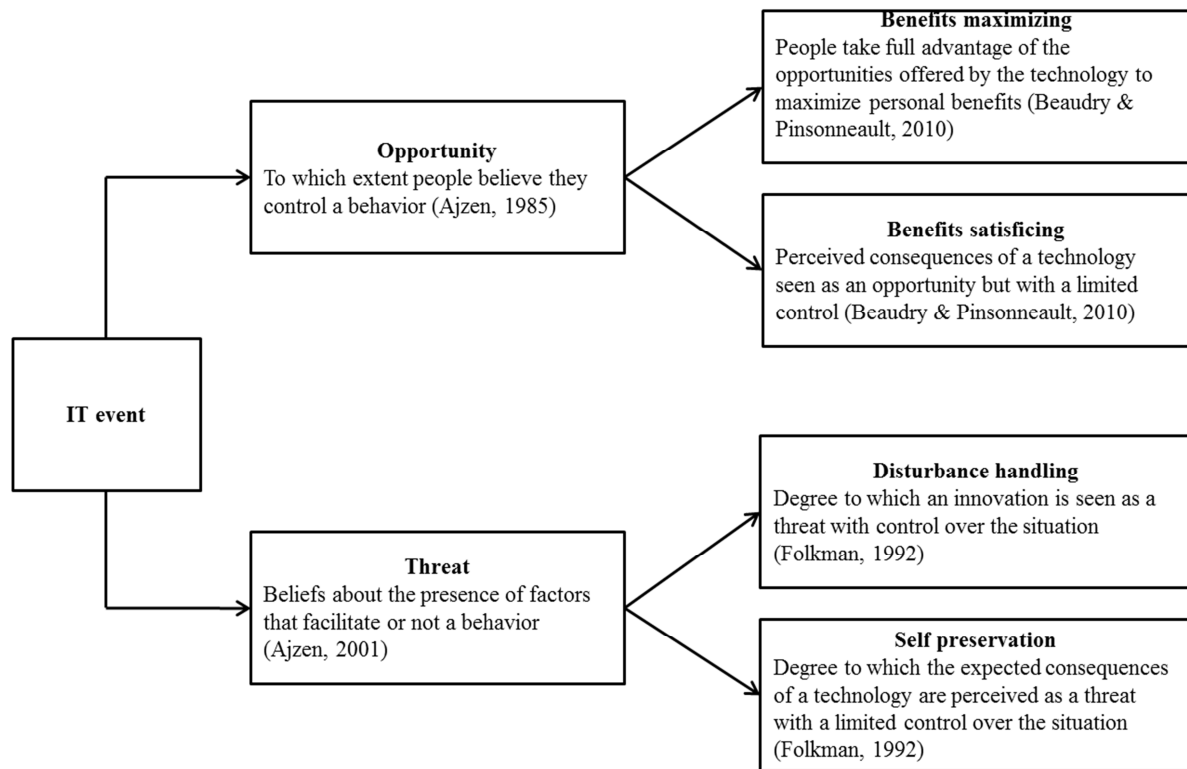


Figure 60: Coping Model of User Adaptation (Beaudry & Pinsonneault, 2010)

Theory and methodology	Main advantages	Main limits
<p>Beaudry & Pinsonneault, 2010 (The Coping Model of User Adaptation—CMUA)</p> <p>Study 1: N = 9 Study 2: N = 8 (Two-hours semi-structured interviews)</p> <p>Technology: Banking sector</p> <p>Definition: The CMUA provides a rich understanding of user behaviors and predicts how and why users will adapt to the technology, the work, and to themselves</p>	<p>- The CMUA focuses on both positive and negative emotions associated with technologies (Beaudry & Pinsonneault, 2010)</p>	<p>- The generalizability of CMUA needs to be further investigated with other technologies and samples (Beaudry & Pinsonneault, 2010)</p> <p>- The influence of social factors on user adaptation must be further investigated (Beaudry & Pinsonneault, 2010)</p> <p>- Longitudinal studies are required (Beaudry & Pinsonneault, 2010)</p>

Table 76: Coping Model of User Adaptation (Beaudry & Pinsonneault, 2010)

Venkatesh et al., 2012 (Unified Theory of Acceptance and Use of Technology 2—UTAUT 2)

2)

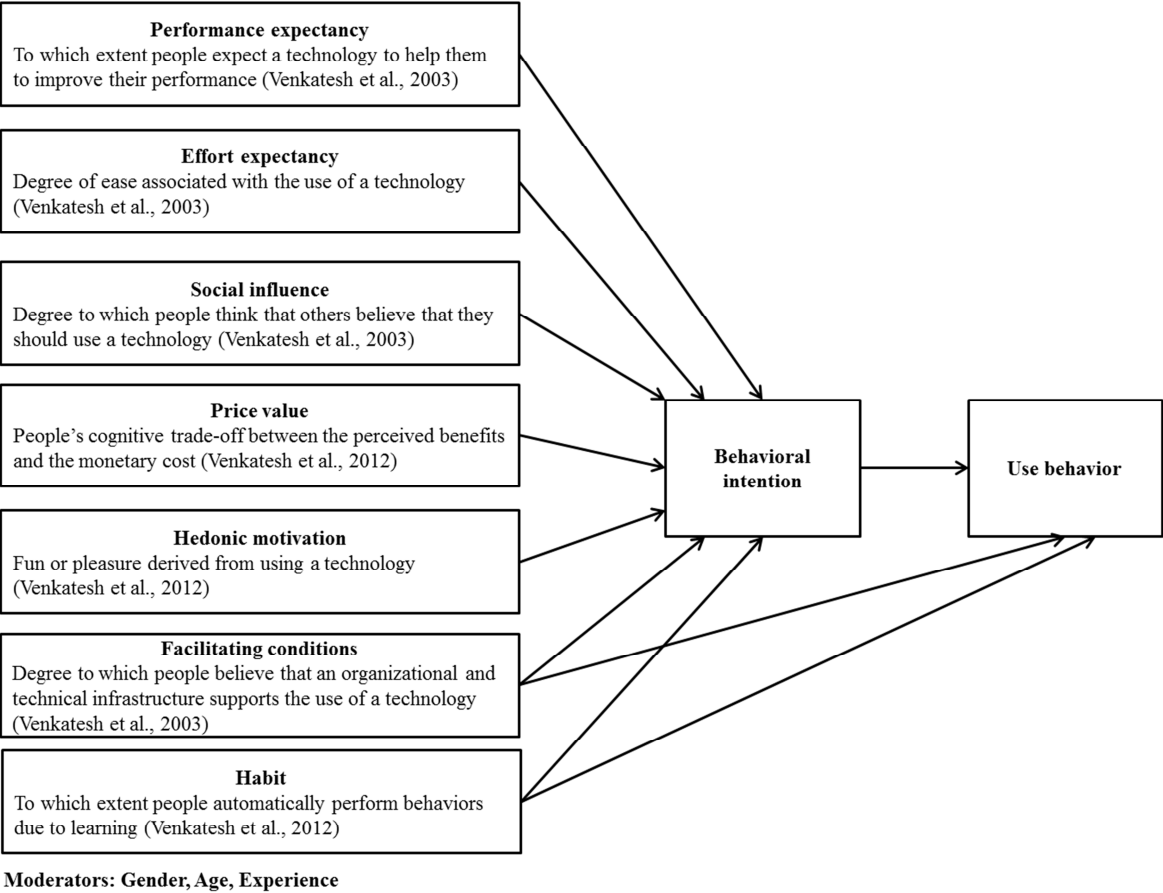


Figure 61: Unified Theory of Acceptance and Use of Technology 2 (Venkatesh et al., 2012)

Theory and methodology	Main advantages	Main limits
<p>Venkatesh et al., 2012 (Unified Theory of Acceptance and Use of Technology 2—UTAUT 2)</p> <p>Study: N = 1,512 (two-stage online survey)</p> <p>Technology: Mobile Internet</p> <p>Definition: The UTAUT 2 is the UTAUT’s extended model with less scale items and fewer factors</p>	<p>- The UTAUT 2 studies hedonic motivations (Venkatesh et al., 2012)</p>	<p>- The UTAUT 2 has limits regarding the generalizability and sample distribution (Venkatesh et al., 2012)</p> <p>- Personal traits, like personal innovativeness, are not studied (Venkatesh et al., 2012)</p>

Table 77: Unified Theory of Acceptance and Use of Technology 2 (Venkatesh et al., 2012)

Lowry et al., 2013 (Hedonic-Motivation System Adoption Model—HMSAM)

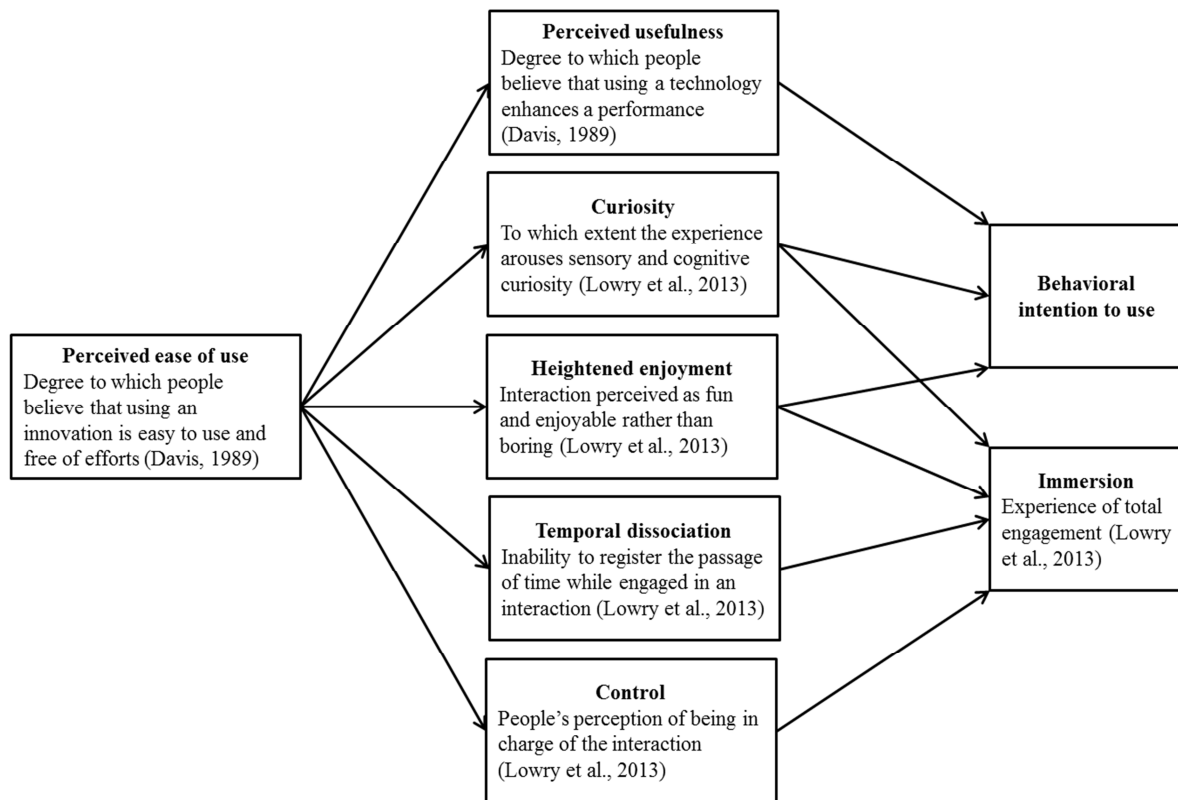


Figure 62: Hedonic-Motivation System Adoption Model (Lowry et al., 2013)

Theory and methodology	Antecedents of adoption	Main advantages	Main limits
<p>Lowry et al., 2013 (The Hedonic-Motivation System Adoption Model—HMSAM) Study 1: N = 243 Study 2: N = 212 (US samples) Technology: 1: Scenarios and storyboards for gaming experiences 2: Actual games in a controlled laboratory experiment Definition: The HMSAM explains the adoption of hedonic-motivation systems (e.g., online games, virtual worlds, online shopping, etc.)</p>	<ul style="list-style-type: none"> - TAM's variables - Control - Curiosity - Heightened enjoyment - Focused immersion - Temporal dissociation 	<ul style="list-style-type: none"> - The HMSAM predicts hedonic technologies adoption (Lowry et al., 2013) - Enjoyment is a stronger predictor of intentions than PU (Lowry et al., 2013; Agarwal & Karahanna, 2000; Agarwal & Venkatesh, 2002; Davis, 1989; Davis et al., 1989; Davis et al., 1992; Koufaris, 2002; Venkatesh, 1999) 	<ul style="list-style-type: none"> - Other intrinsic motivations must be tested (Lowry et al., 2013) - The HMSAM is developed and tested mostly in gaming contexts (Lowry et al., 2013)

Table 78: Hedonic-Motivation System Adoption Model (Lowry et al., 2013)

Appendix 1C: Main articles on perceived well-being

Publication and methodology	Main results	Research directions
<p>Antecedents of individual well-being (Singh & Arora, 2010)</p> <p>Methodology: Qualitative and quantitative research (N = 300; India)</p>	<p>- Antecedents of well-being: physical, activity, economic, occupational professional, education, environment, experience, spirituality, free time, freedom</p>	<p>- Study other cultures and other antecedents (Singh & Arora, 2010)</p>
<p>When consumer well-being meets small business ownership: transforming financial service systems to eradicate disparate treatment and discrimination (Bone et al., 2012)</p> <p>Methodology: Zaltman's (1997) Metaphor Elicitation Technique (N = 39)</p>	<p>- Antecedents: income, social status</p> <p>- Minorities feel more stressed and oppressed whereas majorities perceive their relationships as more balanced, emancipated and free</p>	<p>- Increase the number of respondents (Bone et al., 2012)</p> <p>- Study other antecedents (Bone et al., 2012)</p>
<p>Antecedents of well-being: a study to examine the extent to which personality and emotional intelligence contribute to well-being (Higgsa & Dulewicz, 2014)</p> <p>Methodology: Quantitative surveys (N = 156; executive managers and students)</p>	<p>- Antecedents of well-being: resilience, conscientiousness, self-awareness and interpersonal sensitivity, personality, emotional factors, interpersonal relationships, helping others, physical health, learning ability, personal growth <i>inter alia</i> influence well-being (Seligman, 2003)</p>	<p>- 80% of the variance is not explained; thus, other antecedents of well-being must be studied (Higgsa & Dulewicz, 2014)</p> <p>- Find a wider sample to improve the generalization of the results (Higgsa & Dulewicz, 2014)</p>

Publication and methodology	Main results	Research directions
<p>Conceptualizing Transformative Service Research (Anderson & Ostrom, 2015)</p> <p>Methodology: Study theories of social structure and ecosocial environments</p>	<ul style="list-style-type: none"> - Well-being influences services and their success - Antecedents: consumer-centric, experiential, co-creation strategies, services - A lack of control decreases well-being: consumers feel disadvantaged with decreased knowledge 	<ul style="list-style-type: none"> - Personal attributes must be further studied since people and environments are both linked to well-being (Anderson & Ostrom, 2015)
<p>Attitudes towards personal and shared space during the flight (Ahmadpour et al., 2016)</p> <p>Methodology: Real-time flight experiences with surveys (N = 16)</p>	<ul style="list-style-type: none"> - Four types of attitudes: adjust, avoid, approach, shield - Concerns: control, privacy, connectedness, tolerance - Other antecedent: design of the seat 	<ul style="list-style-type: none"> - Small sample (Ahmadpour et al., 2016) - Lack of data regarding passenger activities during a flight (Ahmadpour et al., 2016)
<p>Does raising value co-creation increase all customers' happiness? (Hsieh et al., 2016)</p> <p>Methodology: Quantitative surveys (N = 602; customers of travel agencies)</p>	<ul style="list-style-type: none"> - Happiness is a state of well-being, contentment, and a central human goal - Customer citizenship behavior relates positively to others' well-being - Antecedents: service performance, contribution to others' well-being - Service quality increases happiness 	<ul style="list-style-type: none"> - Convenience sample (Hsieh et al., 2016) - Not applied to other industries (Kyriakopoulos & Moorman, 2004)

Publication and methodology	Main results	Research directions
<p>Antecedents and consequences of co-creation in credence based service contexts (Kasnakoglu, 2016)</p> <p>Methodology:</p> <ul style="list-style-type: none"> - N = 45 (quantitative study; 21 physicians and 24 patients) - N = 20 (qualitative interviews; 10 professors and 10 students) 	<ul style="list-style-type: none"> - Consumer well-being and outcomes of services are linked - The well-being of co-creation partners influences the entire consumption experience (Sirgy & Lee, 2006) 	<ul style="list-style-type: none"> - Only two service contexts are studied (Kasnakoglu, 2016) - Longitudinal studies are recommended (Kasnakoglu, 2016) - Positive/negative relationships can evolve (Berry, 1995)
<p>Feeling well by being together: Study of Swedish auditors (Umans et al., 2016)</p> <p>Methodology: Quantitative surveys (N = 207; Swedish auditors)</p>	<ul style="list-style-type: none"> - Three parts of well-being: job satisfaction, life balance, and life satisfaction 	<ul style="list-style-type: none"> - Further research must explore other factors like personalities (Umans et al., 2016)
<p>How am I doing? Perceived financial well-being, its potential antecedents, and its relation to overall well-being (Netemeyer et al., 2017)</p> <p>Methodology: N1 = 619 (Survey Sampling International (SSI) online panel); N2 = 554 (SSI online panel); N3 = 106 (MTurk workers)</p>	<ul style="list-style-type: none"> - Antecedents of perceived financial well-being: current finances and financial goals 	<ul style="list-style-type: none"> - Future research must focus on other types of well-being than only the financial one (Netemeyer et al., 2017).

Publication and methodology	Main results	Research directions
<p>Le canal de distribution est-il source de bien-être pour le consommateur ? Une application à l'expérience d'achat de fruits et légumes [English : Is the distribution channel a source of well-being for consumers? An application to the fruit and vegetable buying experience] (Gonzalez et al., 2017)</p> <p>Methodology: Quantitative survey (N = 455; France)</p>	<p>- Antecedents: utility, hedonism, social values, quality, consumer identification to the distribution channel</p>	<p>- Other distribution channels and contexts must be studied (Gonzalez et al., 2017)</p> <p>- Other antecedents could be studied, such as satisfaction over time, motivations, frequency, social interactions (Gonzalez et al., 2017)</p> <p>- Longitudinal studies could bring out other insights (Gonzalez et al., 2017)</p>
<p>Understanding social marketing and wellbeing: A review of selective databases (Bhat et al., 2019)</p> <p>Methodology: Systematic review process regarding a literature review of 94 articles on social marketing and well-being</p>	<p>- Dimensions of well-being: social (social integration, contribution, coherence, actualization acceptance), hedonic (satisfaction, pleasure, enjoyment; Marks & Shah, 2005), and aspects of personal development and well-being (engagement in life, social cohesion, curiosity, autonomy, fulfilment, overall health, longevity, resilience, ability to cope with adverse circumstances; Ryan & Deci, 2001; Joshanloo & Ghaedi, 2009; Joshanloo et al., 2012)</p>	<p>- Future research must employ more empirical and mixed research approaches in social marketing and well-being (Bhat et al., 2019)</p> <p>- Future research must establish a reliable measure of well-being, as the existing scales differ in dimensions and are limited to few constructs (Luca & Suggs, 2013)</p> <p>- Only 29 articles analyze the impact of well-being on behavior change, so longitudinal studies must be conducted (Bhat et al., 2019)</p>

Table 79: Summary of research on consumer well-being in the literature

Appendix 1D: Main articles on the link between perceived well-being and technologies

Publication and methodology	Main results	Research directions
<p>Smart shopping carts: How real time feedback influences spending (Van Ittersum et al., 2013)</p> <p>Methodology:</p> <ul style="list-style-type: none"> - N1 = 66 (university students with credit for participating) - N2 = 194 (professional panel of American responsible for most of their household grocery purchases) - N3 = 198 (shoppers at the beginning of their shopping trip in a grocery store in Atlanta) 	<ul style="list-style-type: none"> - Real-time spending feedback increases purchasing hedonic and national products, and improves the shopping experience by reducing the stress of keeping track of total spending - Positive feelings increase the intention to return to a store but a bad shopping experience does not decrease the intention to return to the store 	<ul style="list-style-type: none"> - Future research must examine whether and how real-time feedback influences other behaviors linked to health (Van Ittersum et al., 2013)
<p>Surveying the comfort perception of the ergonomic design of Bluetooth earphones (Chiu et al., 2014)</p> <p>Methodology: 4 Bluetooth earphones (N = 198)</p>	<ul style="list-style-type: none"> - For earplugs: well-being is influenced by the shape and elasticity - For ear-hooks: the adjustable tail length is an important asset 	<ul style="list-style-type: none"> - Other variables must be studied (Chiu et al., 2014) - Studies must be done before and after use, and not only after 30 minutes of test (Chiu et al., 2014)
<p>Exploring the impact of mobile money services on marketing interactions in relation to consumer well-being in subsistence marketplaces – lessons from rural Cambodia (Fang et al., 2014)</p> <p>Methodology: Qualitative interviews (N = 35; Cambodia)</p>	<ul style="list-style-type: none"> - Well-being is enhanced through accessibility, lesser task complexity, no intermediation - In terms of social network relationships, well-being is enhanced with interpersonal interaction, social groups, cultural levels 	<ul style="list-style-type: none"> - Construct suitable well-being measures to test on a larger sample size (Fang et al., 2014) - Reproduce this study in other countries to do cross-country comparison research (Fang et al., 2014)

Publication and methodology	Main results	Research directions
<p>How to encourage social innovations: A resource-based approach (Sanzo-Perez et al., 2015)</p> <p>Methodology: Quantitative e-mail questionnaire (N = 325; people in charge of foundations' decision-making)</p>	<ul style="list-style-type: none"> - Well-being is improved with society's capacity to act - Co-creation activities improve feelings of well-being by improving abilities 	<ul style="list-style-type: none"> - Focus on one innovation at a time (Sanzo-Perez et al., 2015) - Find potential moderators of the links between the variables (Sanzo-Perez et al., 2015)
<p>An examination of mobile app usage and the user's life satisfaction (Linnhoff & Smith, 2017)</p> <p>Methodology: Online survey programmed in Qualtrics (N = 107; US college students)</p>	<ul style="list-style-type: none"> - Women spend more time than men on mobile apps - The more (less) apps are used, the lower (higher) is the life satisfaction - Social media and using spare time well improve life satisfaction 	<ul style="list-style-type: none"> - Deepen the relationship between app usage and happiness: app usage may contribute to dissatisfaction with life, or unhappy people might be using apps as a distraction (Linnhoff & Smith, 2017)
<p>Does power posing affect gerontechnology adoption among older adults? (Teh et al., 2017)</p> <p>Methodology: Between-subjects experimental study (N = 60; Mean age = 66.2 years)</p>	<ul style="list-style-type: none"> - The experience of feeling powerful implies greater adoption of new technologies, with increased PEU, PU, and positive feelings 	<ul style="list-style-type: none"> - Focus on technologies targeted to younger generations (Teh et al., 2017)
<p>Getting By or Getting Ahead on Social Networking Sites? The Role of Social Capital in Happiness and Well-Being (Munzel et al., 2018)</p> <p>Methodology: Quantitative research (N = 2,116; online survey; Facebook users from France and Spain)</p>	<ul style="list-style-type: none"> - Antecedents of happiness and well-being: size and intimacy of social networks, through social capital - Importance of getting ahead (i.e., bridging social capital) than getting by (i.e., bonding social capital) among users with novel 	<ul style="list-style-type: none"> - Deepen perceived intimacy and relationship closeness (Reis & Franks, 1994) - Study other operationalizations of well-being (Paim, 1995) - Study other antecedents like usage intensity

Publication and methodology	Main results	Research directions
	information and experiences	(Valkenburg & Peter, 2009) or privacy concerns (Jiang et al., 2013) - Different sampling methods must be employed (Munzel et al., 2018)
<p>An empirical comparison of consumer innovation adoption models: Implications for subsistence marketplaces (Hasan et al., 2019)</p> <p>Methodology: Quantitative surveys (N = 320; Bangladesh)</p>	<p>- Enjoyment has the strongest influence on intentions</p>	<p>- Create a hybrid model (Hasan et al., 2019)</p> <p>- Compare new models with existing models (Hasan et al., 2019)</p> <p>- Study other contexts and cultures (Hasan et al., 2019)</p>

Table 80: Summary of research on technologies and consumer well-being in the literature

Appendix 2: Article 1 (*An exploratory qualitative analysis of the IoT technology acceptance: the roles of technology and self-improvement benefits, perceived risks, and user personalities*)

Appendix 2A: Emailing

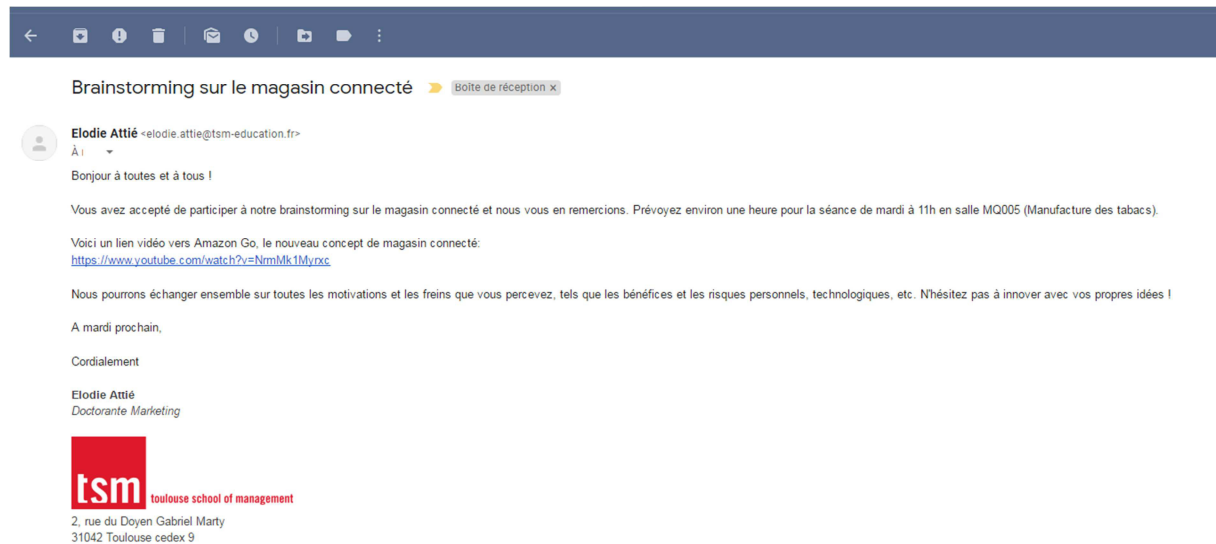


Figure 63: Example of emailing for the qualitative survey

Appendix 2B: Scenario

We started the discussion group with these introductory words: “Thank you for taking part in this discussion group. You will have time on your own to write your thoughts, then we will discuss together what you wrote. We are here to talk about the Internet of Things and smart technologies. The IoT includes physical connected things, like smart watches, smart fridges, etc. and virtual connecting things like wireless networks that identify, collect, store and exchange the data, and which can interact together, anytime and anywhere.”

Then, according to the study, we detailed the topic with examples and videos for each study: “In this research, we focus on smart connected objects which are considered as any object that can connect and be controlled thanks to your smartphone, like connected speakers, connected cars, connected watches, and so on –we do not consider smartphones for this study- (study 1), sleep apps which are programmed to wake you up at the end of your last sleep cycle, sometimes earlier than your time initially programmed (study 2), smart homes which are equipped with sensors fixed on furniture and home equipment to connect everything (study

3), or smart stores which are interactive retail systems delivering services for consumers and employees through a network of smart devices (study 4).”

Each participant then introduced themselves with their name and job occupation.

Thereupon, we did a warm-up with a daily life problem not linked to the context of study like tips to review midterms, travelling alone or with friends, ghosting people on social networks.

Then, we launched the discussion about our topic: “So we are here to talk about smart connected objects (study 1), sleep apps (study 2), smart homes (study 3) or smart stores (study 4), please write anything that goes through your mind when you think about this technology, positive and negative points, and any questions. For example, do you know what it is? How would you define it? How many of you have already used this technology? And still use it today? Why do you use it? Or why would you not use it? What do you like, or do not like about it?”

Once they are done writing down their ideas, we conducted the group discussion. By turn, each participant says what they wrote and we put it on a board so that everyone can see. The discussion became more spontaneous at that moment, since users and non-users started to share their visions and personal experiences. We only reformulated some answers and relaunched some ideas when it did not seem to be clear to everyone or when it seemed interesting for the study. With the respondents, we categorized their ideas into groups. Then, respondents selected the groups they wanted to deepen and wrote again their judgements and thoughts. During a last group discussion time, they share what they have written to deepen some ideas. We also asked them to evaluate the importance of each idea from 1 (strongly disagree) to 5 (strongly agree) to define average scores of importance for each idea. Finally, the participants were thanked for their time.

Appendix 2C: Categorization of the main attributes

Study 1: Smart connected objects

Summary of the discussion: First, some participants mention the fact that smart connected objects sound **useful** (or not useful) to them. Participant 2 says that he “[used] it a lot because it’s very useful for [him] in [his] daily life” whereas others, like participant 1 says: “For me, I cannot imagine why I would need to use one”. “It might help to get in touch with other people probably, no?” (participant 9). “I can find any news I need, when I need it, and wherever I am, just by looking at my wrist, it’s handy” (participant 7). We can see during the conversation that each time a participant gives an advantage about using smart connected objects (e.g. exchange information, do more sport, get news, etc.), people could comment by saying “ok, yes, it’s useful” showing that the first motivation to use a smart connected object is its perceived usefulness. We also see that people working in the IoT domain insist more on usefulness than others, as if to convince. Moreover, non-users seem to have a negative idea of how smart connected objects work, finding them **harder to use**: “I don’t think I could use that, it looks difficult to use” (participant 10). Actual users reassure them, saying “no, it’s easier than smartphones” (participant 4) or “no it’s very easy once it’s connected to your smartphone then you control it with your smartphone. You know how to use your smartphone? Then using smart objects is a game!” (participant 8). The idea of playing, having fun and of a certain sense of **well-being** comes along naturally: “I like it, it’s fun” (participant 5); “I do more sport since I have my watch, it relaxes me at weekends” (participant 3); “I feel good when it connects to my smartphone you know, like wow there it works, I can have fun now. Like you know, I’m a kid, time for fun!” (participant 8). We can see that smart connected objects are like toys to adults, attracting them and giving them fun and some kind of curiosity: “I like new things, I like to try at least” (participant 4); “I’d like to try new types of smart connected objects, just to see” (participant 4). Others are not attracted at all: “I’m not really into new technologies; it’s not for me, I don’t know...” (participant 3); “I really don’t want to try one” (participant 9). We see that users are more attracted to new technologies, showing some signs of **innovativeness**, whereas non-users are recusant to use smart connected objects. “It looks like me, it’s part of my image and it makes me feel good” (participant 8). **Social influence** seems to play also an important role into smart connected objects acceptance and use: “all my friends have connected speakers, I had to have one, and it’s too cool” (participant 5). Furthermore, some of the users admit they spend lots of time on

their smart connected objects, like participant 7: “I can’t help myself but use it all the time you know, to check anything really, I’m a bit dependent in some ways...” Reactions would be very different according to the participant and especially to family status. Parents would show lots of fear of a possible addiction: “when we see how kids are addicted to their smartphone, with these things coming out, it’s going to be even worse!” (participant 1). Finally, **privacy** seems to be the main concern in using or not smart connected objects: “I don’t know how it works when you give all your contact information to an application, but when it’s free you know that they are sold right away to anybody! No trust!” (participant 6); “I am concerned about that, it’s my life, I want to control it. I need to, it’s normal!” (participant 2). “At least, when you pay each month, I hope that it protects personal information...” (participant 10). Non-specialists of the IoT seem to be interested about these issues: “I saw this TV show where applications would sell everything about you even when they would be quite expensive, so private life... You know, at the time you give information about you, it’s lost, it’s not yours anymore. You cannot control the Internet.” (participant 9). “For me, I don’t care, it’s not like I’m Beyoncé or someone famous so who cares about me, so it can only be useful to target or something” (participant 3). The question of privacy is really an issue for all participants, some decide not to care too much about it, seeing it as business, and others take it more seriously and do not want companies to sell anything about them. The analysis of the discussion group brings out themes that we summarized in the following table. We counted how many times an idea appears by individual and into what theme it could be linked to.

Category	Ind. 1	Ind. 2	Ind. 3	Ind. 4	Ind. 5	Ind. 6	Ind. 7	Ind. 8	Ind. 9	Ind. 10	TOTAL
1. Social image	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	80%
- Social image	3	0	1	3	0	0	1	2	2	1	
- Other people	5	0	5	1	0	1	2	3	3	2	
- Friends	2	0	3	1	0	1	1	3	0	2	
- Colleagues	0	0	1	0	0	3	3	2	0	0	
- Professional status	2	0	0	0	0	2	3	3	0	0	
- Snob effect	3	0	0	0	0	0	0	1	2	0	
- To show off	1	0	0	0	0	1	0	0	3	1	
SUB-TOTAL	16	0	10	5	0	8	10	14	10	6	79
2. Utility	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	100%
- Useful	1	5	4	6	4	3	2	2	1	5	

- To communicate	0	0	1	2	3	2	3	1	0	2	
- To give information	0	1	1	2	2	3	2	0	0	0	
- To get some news	0	5	0	1	3	2	4	0	0	1	
- To stay in touch	0	0	2	1	1	1	3	1	0	2	
- To share information	0	1	1	3	0	1	0	2	0	1	
- Easy to use	0	2	0	1	2	1	3	1	0	3	
- Hard to use	1	0	1	0	0	0	0	0	2	0	
SUB-TOTAL	2	14	10	16	15	13	17	7	3	14	111
3. Privacy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	90%
- Privacy	3	2	2	1	1	2	1	2	3	0	
- Confidence	4	2	2	1	0	4	0	3	4	0	
- Database	1	0	1	2	2	3	4	3	1	0	
- Scared (how the data is used)	3	1	2	3	0	2	1	2	5	0	
SUB-TOTAL	11	5	7	7	3	11	6	10	13	0	73
4. Price and privacy	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	90%
- Free application = data sold to anyone	1	2	1	0	3	0	0	0	3	1	
- We have to pay for a service so they protect our privacy	0	1	1	0	2	0	1	1	1	0	
- I like to know that I can deactivate my account anytime	1	1	2	1	3	0	1	0	1	1	
SUB-TOTAL	2	4	4	1	8	0	2	1	5	2	29
5. Well-being and bad-being	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	100%
- Fun	0	1	1	2	1	1	2	2	0	2	
- Makes me feel good	0	0	0	0	1	1	1	2	0	1	
- Makes me happy	0	0	0	0	0	0	1	1	0	2	
- Quality of life	0	1	0	0	2	1	2	1	0	3	
- Motivates for sport	1	2	1	0	0	1	3	2	0	2	
- Dependence	4	1	3	1	0	1	0	1	2	1	
- Stress	3	1	2	0	0	2	0	0	2	0	

- Health	4	5	2	1	2	1	0	2	1	0	
SUB-TOTAL	12	11	9	4	6	7	9	11	5	11	85
6. Innovativeness	No	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes	70%
- Try new technologies	0	1	2	1	2	1	0	1	0	1	
- Capacity of using one	0	1	1	0	1	0	0	1	0	1	
SUB-TOTAL	0	2	3	1	3	1	0	2	0	2	14
7. Attitude	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	90%
- I use SCO everyday	0	1	0	0	1	1	1	0	0	1	
- I would like to try one	0	0	1	0	0	0	0	0	0	0	
- Try other SCO	0	2	0	0	1	1	2	0	0	3	
- I would not use one	1	0	0	1	0	0	0	0	3	0	
SUB-TOTAL	1	3	1	1	2	2	3	0	3	4	20
TOTAL	44	39	44	42	30	43	47	45	39	39	412

Table 81: Categorization of the main attributes of SCO

Study 2: Sleep apps

Summary of the discussion: Some participants find the app **useful**, using the words “useful, practical, effective, efficient” (participant 2) and “fast to access information to save time and increase productivity” (participant 6). For others, it is more of a “superfluous, futile” (participant 4), “secondary” (participant 8), “ostentatious and paradoxical gadget that would not help them in their daily lives” (participant 2). Moreover, the app seems **easy** to understand and use, like they say: “rather easy to use, fluid, functional” (participant 1), “adapted, adaptable and simple with a clever ease of use” (participant 2), notably thanks to “automatic coordination and simple automated links” (participant 6). If the app seems accessible to some participants, others seem more sceptical, citing a “complex and complicated system rather difficult to conceive” (participant 3) “not accessible to everyone (e.g., seniors...)” (participant 9). Besides, the sleep app seems to improve **well-being** and is thus “a good idea” (participant 8) because it looks “interactive, intuitive, fun and playful” (participant 2). Some mention the terms “sympathetic” (participant 5), “relief” (participant 7) and “pleasant to be in a bubble and get some positive energy” (participant 1). Some respondents, who seem to be more **innovative**, point out the “improvement of my life and daily routines with new modes of smart automation that revolutionize ways of living in a more optimized way” (participant 8) and which offers “new possibilities that make life easier” (participant 1). This “modernity” (participant 8) does not represent a brake, but rather “a progress for the future” (participant 8) through “a smart development adapted to the evolution of our growing connected lifestyles” (participant 1). On the contrary, others seem more reluctant, saying that they “don’t really want to use this kind of app” (participant 3). For them, the app seems to have “alienating characteristics, leading to oppressive feelings” (participant 7). Some participants speak of “dehumanization” (participant 9) and “a connected nightmare leading to laziness” (participant 4), “dullness and some psychological stress if not used with moderation” (participant 10). Putting their phone under their pillows also scare many respondents and they refer to **health risks** with the “diffusion of electromagnetic radiations which are a harmful danger” (participant 7). Others also mention the “high risk of dependence and addiction” (participant 10). The app shows **trust** issues as well, as it seems “unreliable with risks of bugs and uncertainties” (participant 3). For others, the app looks “safe, trustworthy about its functionalities” (participant 2), “available” (participant 1) and “reassuring” (participant 5). One of the major obstacles to the use of the sleep app remains **privacy concerns**, with the “non-intimate and intrusive” (participant 7) aspects with “confidentiality risks, and traced

management quite risky for its users” (participant 3). “Data security” is cited by almost all respondents, with a fear of “constant surveillance” (participant 4) because the app gives “the impression of being constantly observed even when I sleep” (participant 2) by a “connected big brother” (participant 1). The risks of “increased piracy, espionage by hackers” (participant 10) and “dissemination to third parties” (participant 7) are cited, resulting in a decline of “confidence in the use of the data” (participant 10) and high “privacy concerns” (participant 3). Finally, this app leads to the concept of **quantified-self** by the fact that it allows “self-control” (participant 5), “self-assistance and self-management to control our sleep in the most effective ways” (participant 6). On the contrary, some are afraid of having “less autonomy” (participant 3) and of being unable to control it, using the words “uncontrollable” (participant 1), “out of control” (participant 8), “abusive” (participant 4), and too “authoritarian” (participant 10). The analysis of the discussion group brings out themes that we summarized in the following table.

Category	Ind. 1	Ind. 2	Ind. 3	Ind. 4	Ind. 5	Ind. 6	Ind. 7	Ind. 8	Ind. 9	Ind. 10	TOTAL
1. Usefulness	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes	80%
- Useful	3	1	1	2	0	3	0	2	0	2	
- Practical	1	0	0	0	0	1	0	0	0	0	
- Productivity	0	0	0	0	1	2	0	0	0	0	
- Gain/save time	1	0	0	0	1	1	0	0	0	0	
- Gadget	0	2	0	1	0	0	0	1	0	0	
- Superfluous	0	1	0	1	0	0	0	2	0	1	
SUB-TOTAL	5	4	1	4	2	7	0	5	0	3	31
2. Ease of use	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	90%
- Fluid	1	0	0	1	0	0	0	0	0	0	
- Simple	1	1	0	2	0	2	0	0	0	0	
- Accessibility	0	1	0	0	0	0	1	0	1	0	
- Easy to use	2	1	0	3	1	3	0	0	0	1	
- Hard to use	0	0	1	0	0	0	1	0	0	0	
- Complex	0	0	2	0	0	0	0	0	1	0	
SUB-TOTAL	4	3	3	6	1	5	2	0	2	1	27
3. Well-being	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	100%
- Interactive	0	1	0	0	0	1	0	0	0	0	

- Fun	1	2	0	0	1	0	0	0	0	0	
- Quality of life	1	1	0	0	2	1	0	2	0	1	
- Enjoyment	2	3	0	0	1	1	0	2	0	0	
- Oppressive	0	0	0	0	0	0	1	0	1	0	
- Stress	0	0	1	2	0	0	4	0	1	2	
- Dependence	0	0	1	0	0	0	0	0	1	1	
- Radiation risks	1	1	2	0	0	0	3	1	1	1	
SUB-TOTAL	5	8	4	2	4	3	8	5	4	4	47
4. Privacy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	100%
- Data security	1	1	1	1	2	1	1	3	1	1	
- Technology trust	1	1	0	0	1	0	0	0	1	0	
- Reliability	1	1	1	0	1	0	1	0	0	1	
- Intrusive	0	0	0	1	0	0	1	2	1	3	
- Surveillance	1	0	0	1	0	1	1	0	1	1	
- Confidentiality	0	1	1	0	1	1	2	1	2	2	
- Risks of hacking	0	0	1	1	0	1	0	0	0	2	
SUB-TOTAL	4	4	4	4	5	4	6	6	6	10	53
5. Quantified-self	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	80%
- Control											
- Autonomy	1	0	0	2	1	0	0	1	0	1	
- Assistant	0	0	1	1	0	1	0	0	0	0	
- Self-management	1	0	0	1	0	1	0	1	0	1	
	0	0	0	0	2	1	0	1	1	0	
SUB-TOTAL	2	0	1	4	3	3	0	3	1	2	19
6. Innovativeness	Yes	Yes	Yes	No	Yes	Yes	No	Yes	No	No	60%
- Innovative	1	1	0	0	1	1	0	0	0	0	
- New technologies	1	2	1	0	1	2	0	2	0	0	
- Attractive	1	1	0	0	0	0	0	0	0	0	
- Progress	0	0	0	0	0	0	0	1	0	0	
SUB-TOTAL	3	4	1	0	2	3	0	3	0	0	16
7. Attitude	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	100%
- Good idea	0	0	0	0	0	0	0	1	0	0	
- Usage	0	1	0	1	0	1	0	1	0	0	

- Try the app	1	1	1	0	1	1	1	1	1	1	
SUB-TOTAL	1	2	1	1	1	2	1	3	1	1	14
TOTAL	24	25	15	20	17	27	17	25	14	21	205

Table 82: Categorization of the main attributes of sleep apps

Study 3: Smart homes

Summary of the discussion: According to participants, smart homes are attractive when they are **useful**: “people will be able to access real-time information” (participant 1). Moreover, “smart environments will soon be essential, because people will find them practical and efficient, as it should simplify processes of living” (participant 5). However, if smart homes seem “easy and logical to exist in a near future” (participant 4), “people will need time to learn how to use this new technology” (participant 10). The most **innovative** participants mention the notion of **well-being** since “the IoT is adapting technology to their wishes and envies” (participant 7) as “the IoT should create attractive and ludic environments, improving the way people live” (participant 3). Also, most agree on the fact that “the IoT should increase the comfort we have in our lives, it’s all for a better future” (participant 1). On the opposite, some participants talk about the perceived stress regarding **social life** they would feel in smart homes: “smart environments will decrease the quantity and quality of our relationships, leading to zero real social relationships” (participant 2) or to “new pervert relationships where we know all the information about others and others know everything we share too” (participant 8). On the opposite, others believe that smart homes will improve their relationships: “smart environments should enable us to gain time and thus we can spend this saved time with our family and friends” (participant 1); “I will be more connected to the people I care about” (participant 7). The main brake to the acceptance of smart homes seems to be about **privacy concerns**. “There is this feeling of constantly being spied on and watched by a connected big brother, and this brings paranoia and stress” (participant 8). According to participant 1, “it is dangerous to put all our information accessible by anyone”. One way to decrease this negative perception would be “transparency” (participant 3): “we want to know what they collect then what happens, we want to know the IoT works with us, for us, and not through us” (participant 4). Moreover, regarding **health risks**, participant 6 says that “some people can be very sensitive to these electromagnetic radiations and we have no idea of the impact of these Wi-Fi and Bluetooth networks on our health yet”. Furthermore, we perceive that some participants seem to be more or less predisposed to feel, accept and share feelings of hedonism than others. They are more interested by IoT technologies giving either short or long time feelings of hedonism and entertainment, while improving health: “I’m curious to see where all this goes, I really can’t wait, it makes me happy” (participant 2); “I can imagine myself living in a smart home, it will feel good” (participant 7); “I will love inviting people to this kind of place and have fun with them, like parties and stuff!” (participant 4). On the

opposite, lower **well-being people** seem less enthusiastic and more negative about it: “it is too innovative, it kind of scares me a bit” (participant 10); “I don’t believe this can work” (participant 6); “this will make me feel depressed” (participant 8). The analysis of the discussion group brings out themes that we summarized in the following table.

Category	Ind. 1	Ind. 2	Ind. 3	Ind. 4	Ind. 5	Ind. 6	Ind. 7	Ind. 8	Ind. 9	Ind. 10	TOTAL
1. Utility value	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	100%
- Useful	1	1	1	2	1	1	1	1	1	2	
- Information	1	2	2	1	1	2	1	2	1	3	
- Practical	1	0	0	0	1	1	0	1	0	2	
- Gain time	1	1	0	0	1	0	0	1	0	1	
- Simple	0	0	0	1	0	1	0	1	1	0	
- Easy	1	1	1	1	1	1	1	0	0	1	
SUB-TOTAL	5	5	4	5	5	6	3	6	3	9	51
2. Well-being	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	100%
- Quality of life	1	0	1	0	1	0	1	0	0	2	
- Comfort	1	0	0	0	0	0	1	0	1	1	
- Fun	0	1	1	2	0	0	0	0	0	0	
- Hedonism	0	2	1	3	0	0	0	0	1	1	
- Health	1	1	0	1	1	1	0	0	1	1	
- Stress	0	0	0	0	1	3	0	1	0	0	
- Radiation effects	1	0	0	1	1	2	0	1	1	1	
- Dependence	0	0	1	1	0	1	1	2	1	1	
SUB-TOTAL	4	3	4	8	4	7	3	4	5	7	50
3. Social value	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	No	60%
- Relationships	1	2	0	0	0	0	1	2	1	0	
- Social status	0	1	1	0	0	0	0	1	1	0	
- Image	0	0	1	0	0	0	0	2	0	0	
- Other people	2	2	0	0	0	0	2	1	1	0	
SUB-TOTAL	3	4	2	0	0	0	3	6	3	0	21
4. Privacy	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	80%
- Data collection	1	0	1	1	1	2	0	1	1	2	
- Spy	0	0	0	0	2	0	0	1	1	1	

- Transparency	0	0	2	1	3	1	0	0	0	0	
- Privacy	2	0	3	2	2	3	0	1	1	2	
- Anonymous	1	0	2	0	2	0	0	1	1	1	
SUB-TOTAL	4	0	8	4	10	6	0	4	4	6	46
5. Well-being personality	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	60%
- Curious	0	1	2	3	0	0	2	1	2	0	
- Feeling happy	0	0	1	1	0	0	1	1	1	0	
- Feeling good	0	1	1	2	0	0	2	0	1	0	
- Ability to imagine	0	2	1	1	0	0	2	1	2	0	
SUB-TOTAL	0	4	5	7	0	0	6	3	6	0	32
6. Innovativeness	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	90%
- Innovations	1	1	1	1	2	0	1	3	1	1	
- Future	1	0	1	2	1	0	0	1	1	1	
- Connected world	0	0	1	1	0	0	0	0	0	0	
- Attractive	1	2	1	1	1	0	1	1	0	0	
SUB-TOTAL	3	3	4	5	4	0	2	5	2	2	30
7. Attitude	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	100%
- Adopt	0	1	1	1	0	0	1	1	0	0	
- Try	1	1	0	1	0	0	0	1	1	0	
- Reject	0	0	0	0	1	1	0	0	0	1	
SUB-TOTAL	1	2	1	2	1	1	1	2	1	1	13
TOTAL	20	21	28	31	24	24	18	30	24	25	248

Table 83: Categorization of the main attributes of smart homes

Study 4: Smart stores

Summary of the discussion: Most participants seem to be accepting toward the concept of smart stores: “I want to try one!” (participant 1) or “I wish it could exist in Toulouse” (participant 7). The main asset cited is the **usefulness** of smart stores with an “amount of supplementary and useful information consumers will be able to get, like where is that product, in which size, etc.” (participant 4), “quicker and easier ways to buy products” (participant 3), and “less waiting during the buying process” (participant 8). Moreover, other respondents like participant 9 says that “smart stores will push them to buy more as the buying process will be easier and simpler, decreasing consumer control and thus, increasing bad-being afterwards. It gives an illusion of not spending when we actually are buying”. Another participant details this idea with the following: “companies will find more ways to push us to buy, to control us, to manipulate us” (participant 3). Besides, another concern relates to **health risks** since “smart stores will push everyone to have a smartphone and always be connected, increasing the time spent on technology and addiction risks” (participant 5) and that “we will need to always have battery, this is stressing when you have 1% battery left, imagine if you can’t do anything anymore because of it, we’ll feel completely lost” (participant 9). **Privacy concerns** seem an important risk since “collecting all this data is stressing. Companies have access to everything, to information we don’t even know sometimes and we don’t really know what they do with it” (participant 10). Participant 4 argues that “it is intrusive, companies are making us losing control of managing and sharing our private information little by little and most people don’t see it or don’t care about it”. Further, the **social value** has been mentioned too. Participant 7 talks about “a lack of human contact and thus a lack of social life” whereas participant 6 evaluates that going to a smart store will “give a VIP status to customers”. However, the **well-being value** is a way to reduce those tensions, through “the benefits of personalisation [which] are higher when we give the most accurate and precise information” (participant 8) and it then becomes “a fun and entertaining environment I would love to visit” (participant 6). Finally, some users seem to be more or less predisposed to get, feel, and then use their senses of power over themselves, people or the brand. “One of the main reasons why I want to buy in a smart store is to manage my purchase”, explains participant 7. Lower empowered users are reassured with a very high ethical value: “the policies of privacy and use should be clear and transparent because we lack control” (participant 5). Moreover, the price-to-quality ratio is important to them, as they are generally undecided: “I don’t know, well, it is expensive, I need to know if I really need it, I

don't think so" (participant 9). The analysis of the discussion group brings out themes that we summarized in the following table.

Category	Ind. 1	Ind. 2	Ind. 3	Ind. 4	Ind. 5	Ind. 6	Ind. 7	Ind. 8	Ind. 9	Ind. 10	TOTAL
1. Social value	No	Yes	No	Yes	Yes	Yes	Yes	No	No	No	50%
- Social life	0	1	0	1	0	0	1	0	0	0	
- Human contact	0	1	0	2	0	0	1	0	0	0	
- Social status	0	0	0	0	1	1	0	0	0	0	
- Social image	0	1	0	0	1	1	0	0	0	0	
SUB-TOTAL	0	3	0	3	2	2	2	0	0	0	12
2. Usefulness	No	No	Yes	Yes	No	No	No	Yes	Yes	Yes	50%
- Information	0	0	1	2	0	0	0	2	0	2	
- Useful	0	0	1	3	0	0	0	1	1	1	
- Fast service	0	0	1	1	0	0	0	1	1	0	
- Easy	0	0	1	0	0	0	0	0	1	0	
- Gain time	0	0	0	1	0	0	0	1	2	0	
SUB-TOTAL	0	0	4	7	0	0	0	5	5	3	24
3. Well-being	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	No	70%
- Fun	1	1	0	0	0	1	0	0	0	0	
- Entertaining	1	1	0	0	0	2	0	1	0	0	
- Personalization	0	0	0	0	0	0	0	1	0	0	
- Bad-being	0	0	0	0	1	0	2	0	1	0	
- Stress	0	1	0	0	1	0	2	0	2	0	
SUB-TOTAL	2	3	0	0	2	3	4	2	3	0	19
4. Privacy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	100%
- Data	2	2	1	2	2	1	2	1	1	2	
- Privacy	1	1	1	2	0	1	1	1	1	1	
- Intrusive	1	1	0	3	1	0	1	0	0	1	
- Transparency	0	1	1	1	0	2	0	0	0	0	
SUB-TOTAL	4	5	3	8	3	4	4	2	2	4	39
5. Empowered personality	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	70%
- Control	2	0	1	1	1	0	1	2	1	0	

- Power	1	0	1	1	1	0	0	1	0	0	
- Connected	2	0	0	1	1	0	0	2	0	0	
- Self-management	3	0	1	0	0	0	2	1	0	0	
- Feeling lost	0	0	0	0	0	0	0	0	1	0	
SUB-TOTAL	8	0	3	3	3	0	3	6	2	0	29
6. Attitude	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	100%
- Intention to visit	1	1	0	0	1	1	1	1	1	0	
- Intention to buy	0	0	0	0	0	0	1	1	1	0	
- Become loyal	0	0	0	0	0	0	1	0	1	0	
- Reject	0	0	1	1	0	0	0	0	0	1	
SUB-TOTAL	1	1	1	1	1	1	3	2	3	1	15
TOTAL	15	12	11	22	11	10	16	17	15	8	138

Table 84: Categorization of the main attributes of smart stores

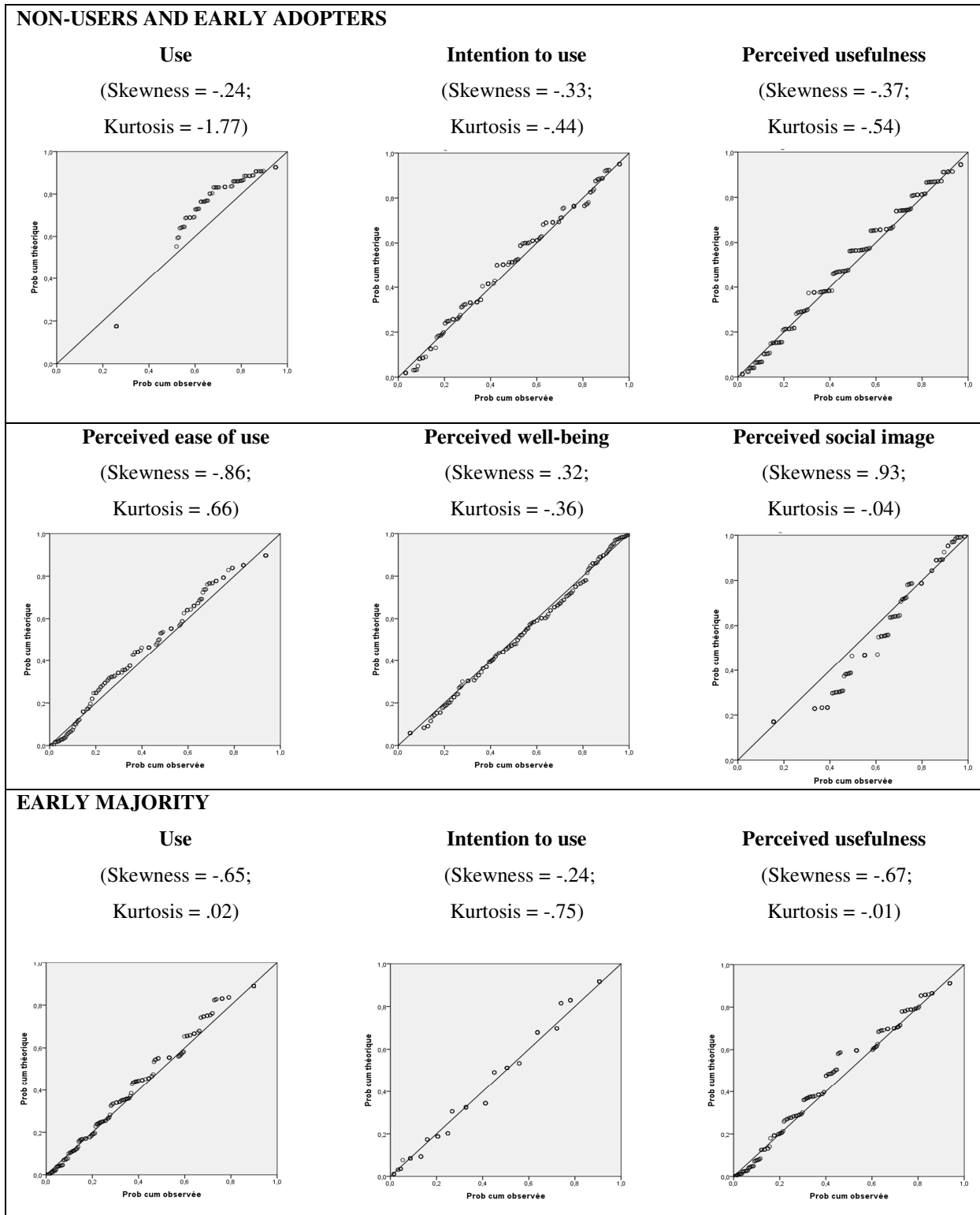
Appendix 2D: Average scores of importance

Attributes	Average score /5
Smart/connected objects	
Well-being	3.50
Privacy concerns	3.50
Social image/influence	2.90
Perceived usefulness	2.70
Perceived ease of use	2.33
Sleep apps	
Well-being	3.88
Privacy concerns	3.88
Perceived usefulness	2.35
Perceived ease of use	2.05
Smart homes	
Well-being	3.10
Privacy concerns	3.10
Utility value	2.90
Smart stores	
Well-being	2.90
Privacy concerns	2.90
Utility value	2.70
Social image/influence	1.95

Table 85: Average scores of importance (*Appendix 2D*)

Appendix 3: Article 2 (*A theoretical model incorporating social influence and cognitive processes to explain the adoption of the Internet of Things and smart connected objects*)

Appendix 3A: Multivariate normality analysis



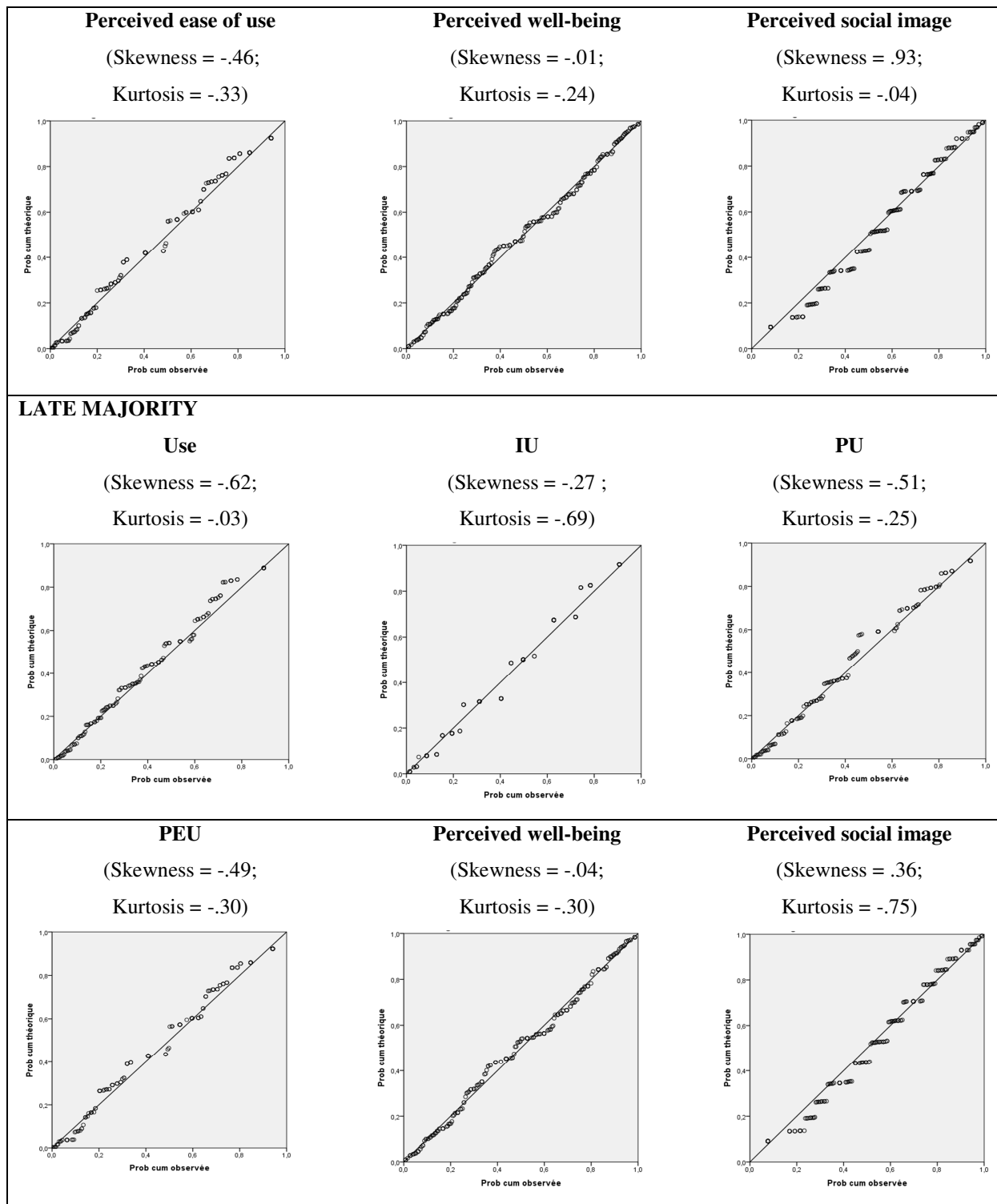


Table 86: Multivariate normality analysis (*Article 2; adoption of SCO*)

Appendix 3B: Moderating effects

Moderator	Effect	S.E.	t	LLCI	ULCI	ΔR ²	F	Hypothesis
NON-USERS AND EARLY ADOPTERS								
Privacy concerns								
H1: IU -> real use								Supported
-1 S.D.	.12	.10	7.34***	.23	.63			
Mean	.10	.06	7.56***	.36	.61	1%	22.35***	
+1 S.D.	.07	.07	7.11***	.38	.68			
H2a: PU -> real use								Not supported
-1 S.D.	.08	.10	5.20***	.33	.74			
Mean	.09	.06	4.10***	.43	.68	0%	31.37***	
+1 S.D.	.09	.07	4.12***	.43	.72			
H2b: PU -> IU								Not supported
-1 S.D.	.46	.07	9.79***	.58	.88			
Mean	.46	.04	8.02***	.68	.86	0%	118***	
+1 S.D.	.44	.05	9.44***	.70	.90			
H3a: PEU -> PU								Supported
-1 S.D.	.48	.07	7.82***	.68	.77			
Mean	.45	.08	7.71***	.61	.71	1%	18.35***	
+1 S.D.	.42	.11	6.58***	.71	.80			
H3b: PEU -> IU								Not supported
-1 S.D.	.20	.07	4.00***	.47	.78			
Mean	.21	.05	4.51***	.53	.74	0%	57.01***	
+1 S.D.	.21	.06	4.57***	.51	.77			
H3c: PEU -> real use								Supported
-1 S.D.	.45	.09	4.33***	.22	.59			
Mean	.43	.06	6.71***	.30	.55	1%	15.53***	
+1 S.D.	.40	.08	5.56***	.29	.61			
Innovativeness								
H1: IU -> real use								Not supported
-1 S.D.	.09	.08	.69*	.41	.75			
Mean	.08	.07	.71*	.42	.70	0%	22.39***	
+1 S.D.	.10	.09	.53*	.35	.73			
H2a: PU -> real use								Supported
-1 S.D.	.09	.07	4.36***	.42	.73			
Mean	.10	.06	4.31***	.47	.73	1%	31.21***	
+1 S.D.	.12	.08	5.07***	.45	.80			

Moderator	Effect	S.E.	t	LLCI	ULCI	ΔR ²	F	Hypothesis	
H2b: PU -> IU									
	-1 S.D.	.45	.05	8.60***	.57	.79		Not supported	
	Mean	.46	.04	8.12***	.59	.77	0%		14.22***
	+1 S.D.	.46	.06	8.27***	.56	.80			
H3a: PEU -> PU									
	-1 S.D.	.45	.07	8.29***	.44	.71		Not supported	
	Mean	.45	.07	8.01***	.44	.74	0%		47.18***
	+1 S.D.	.46	.10	5.77***	.40	.81			
H3b: PEU -> IU									
	-1 S.D.	.18	.06	4.43***	.36	.62		Supported	
	Mean	.21	.07	4.37***	.38	.66	1%		58.65***
	+1 S.D.	.25	.10	4.44***	.34	.74			
H3c: PEU -> real use									
	-1 S.D.	.40	.08	6.22***	.34	.67		Supported	
	Mean	.43	.08	6.17***	.36	.70	1%		16.40***
	+1 S.D.	.46	.12	4.55***	.31	.80			
EARLY MAJORITY									
Privacy concerns									
H1: IU -> real use									
	-1 S.D.	.14	.07	2.45***	.19	.49		Not supported	
	Mean	.14	.05	2.31***	.24	.47	0%		13.92***
	+1 S.D.	.17	.07	2.71***	.21	.52			
H2a: PU -> real use									
	-1 S.D.	.40	.06	7.70***	.36	.62		Not supported	
	Mean	.41	.05	7.07***	.46	.66	0%		47.37***
	+1 S.D.	.41	.07	7.83***	.49	.78			
H2b: PU -> IU									
	-1 S.D.	.02	.07	.49ns	.25	.53		Not supported	
	Mean	.02	.05	.96ns	.28	.50	0%		16.50***
	+1 S.D.	.04	.08	.98ns	.24	.55			
H3a: PEU -> PU									
	-1 S.D.	.39	.06	8.90***	.42	.66		Not supported	
	Mean	.39	.04	8.91***	.49	.69	0%		47.55***
	+1 S.D.	.40	.06	9.23***	.50	.77			
H3b: PEU -> IU									
	-1 S.D.	.13	.07	2.62**	.04	.33		Supported	
	Mean	.11	.05	2.77**	.04	.27			
	+1 S.D.	.09	.08	1.64*	-.02	.29	1%		23.21***

Moderator	Effect	S.E.	t	LLCI	ULCI	ΔR ²	F	Hypothesis
H3c: PEU -> real use								
	-1 S.D.	.16	.07	2.92***	.28	.56		Not supported
	Mean	.16	.05	2.71***	.31	.53	0% 20.59***	
	+1 S.D.	.13	.07	2.61***	.27	.58		
Innovativeness								
H1: IU -> real use								
	-1 S.D.	.17	.08	3.36***	.19	.50		Not supported
	Mean	.17	.06	3.54***	.22	.47	0% 12.91***	
	+1 S.D.	.18	.08	4.11***	.18	.51		
H2a: PU -> real use								
	-1 S.D.	.34	.06	7.26***	.40	.66		Supported
	Mean	.37	.05	6.98***	.44	.65	1% 41.10***	
	+1 S.D.	.39	.07	7.34***	.41	.71		
H2b: PU -> IU								
	-1 S.D.	.02	.06	.87*	.19	.45		Not supported
	Mean	.02	.05	.75*	.20	.41	0% 33.83***	
	+1 S.D.	.09	.07	.70*	.13	-.44		
H3a: PEU -> PU								
	-1 S.D.	.36	.07	8.33***	.30	.57		Supported
	Mean	.39	.05	8.55***	.42	.63	1% 35.50***	
	+1 S.D.	.43	.07	8.11***	.47	.77		
H3b: PEU -> IU								
	-1 S.D.	.10	.07	3.54***	.12	.41		Supported
	Mean	.11	.05	3.11***	.18	.41	1% 8.88***	
	+1 S.D.	.13	.08	4.07***	.17	.49		
H3c: PEU -> real use								
	-1 S.D.	.11	.07	4.10***	.23	.52		Supported
	Mean	.16	.06	4.20***	.31	.54	3% 20.13***	
	+1 S.D.	.19	.08	4.82***	.31	.63		
LATE MAJORITY								
Privacy concerns								
H1: IU -> real use								
	-1 S.D.	.17	.08	3.97***	.17	.51		Not supported
	Mean	.17	.06	2.60***	.23	.48	0% 10.79***	
	+1 S.D.	.16	.08	2.22***	.19	.53		
H2a: PU -> real use								
	-1 S.D.	.39	.07	7.68***	.29	.60		Supported
	Mean	.37	.05	7.90***	.40	.63	1% 27.68***	
	+1 S.D.	.34	.08	7.25***	.43	.76		

Moderator	Effect	S.E.	t	LLCI	ULCI	ΔR ²	F	Hypothesis
H2b: PU -> IU								
	-1 S.D.	.34	.08	4.06***	.17	.51		Not supported
	Mean	.35	.06	5.61***	.23	.48	0% 11.22***	
	+1 S.D.	.36	.09	4.02***	.18	.54		
H3a: PEU -> PU								
	-1 S.D.	.42	.07	3.73***	.35	.64		Not supported
	Mean	.41	.05	2.24***	.45	.67	0% 34.46***	
	+1 S.D.	.41	.07	2.49***	.49	.78		
H3b: PEU -> IU								
	-1 S.D.	.08	.08	2.76ns	.06	.39		Supported
	Mean	.08	.06	2.95ns	.13	.38	1% 5.90***	
	+1 S.D.	.07	.09	3.13ns	.10	.46		
H3c: PEU -> real use								
	-1 S.D.	.19	.07	5.22*	.25	.57		Supported
	Mean	.15	.06	4.30*	.27	.51	1% 13.89***	
	+1 S.D.	.12	.08	4.25*	.20	.54		
Innovativeness								
H1: IU -> real use								
	-1 S.D.	.15	.09	3.28***	.12	.48		Supported
	Mean	.18	.07	3.72***	.19	.47	1% 10.12***	
	+1 S.D.	.21	.09	3.92***	.18	.55		
H2a: PU -> real use								
	-1 S.D.	.33	.07	4.90***	.30	.61		Supported
	Mean	.37	.05	4.63***	.39	.62	1% 28.06***	
	+1 S.D.	.42	.08	4.62***	.38	.71		
H2b: PU -> IU								
	-1 S.D.	.08	.07	3.22*	.09	.40		Supported
	Mean	.10	.05	4.56*	.15	.38	1% 28.62***	
	+1 S.D.	.12	.08	3.41*	.11	.44		
H3a: PEU -> PU								
	-1 S.D.	.41	.07	2.28ns	.25	.56		Not supported
	Mean	.41	.06	1.97ns	.42	.67	0% 31.86***	
	+1 S.D.	.43	.08	1.29ns	.52	.85		
H3b: PEU -> IU								
	-1 S.D.	.07	.08	.95ns	-.08	.24		Not supported
	Mean	.09	.06	1.45ns	-.03	.22		
	+1 S.D.	.09	.08	1.25ns	-.06	.28	.03% 20.69***	

Moderator	Effect	S.E.	t	LLCI	ULCI	ΔR^2	F	Hypothesis
H3c: PEU -> real use								Supported
-1 S.D.	.12	.08	3.34***	.11	.45			
Mean	.15	.06	5.85***	.25	.52	1%	14.12***	
+1 S.D.	.19	.09	5.50***	.32	.67			

*** indicates p -value < .001; ** p -value < .01; * p -value < .1; IU stands for intention of use; PU for perceived usefulness; PEU for perceived ease of use.

Table 87: Details of the moderating effects (*Article 2; adoption of SCO*)

Appendix 4: Article 3 (A longitudinal study to explain the adoption of smart sleep apps with perceived well-being, quantified-self, privacy concerns, and user personalities)

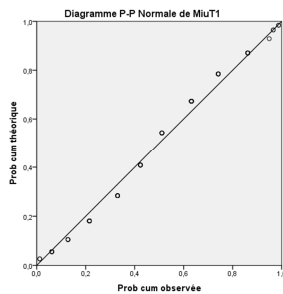
Appendix 4A: Multivariate normality analysis

BEFORE USE

Intention to use

(Skewness = $-.02$;

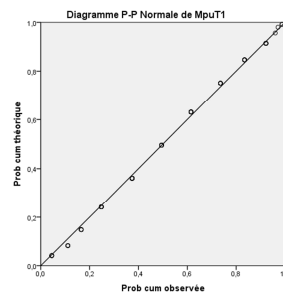
Kurtosis = $-.84$)



Perceived usefulness

(Skewness = $.08$;

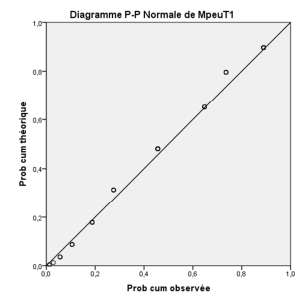
Kurtosis = $-.45$)



Perceived ease of use

(Skewness = $-.54$;

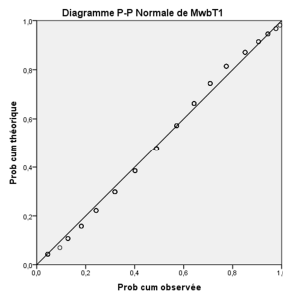
Kurtosis = $.15$)



Perceived well-being

(Skewness = $.01$;

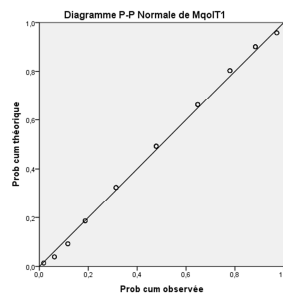
Kurtosis = $-.85$)



Quantified-self

(Skewness = $.26$;

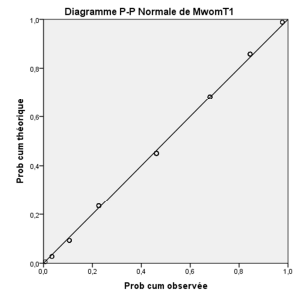
Kurtosis = $-.79$)



Word-of-mouth intentions

(Skewness = $.03$;

Kurtosis = $-.02$)

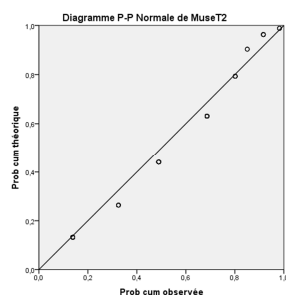


AFTER USE

Use

(Skewness = $.67$;

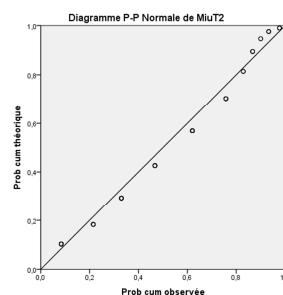
Kurtosis = $-.46$)



Intention to use

(Skewness = $.71$;

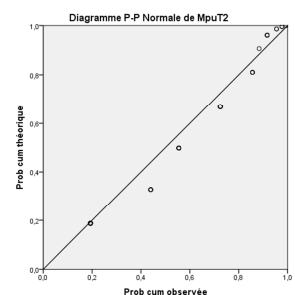
Kurtosis = $-.12$)



Perceived usefulness

(Skewness = 1.26 ;

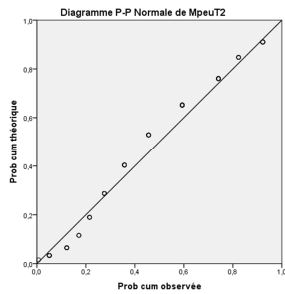
Kurtosis = 1.37)



Perceived ease of use

(Skewness = -.45;

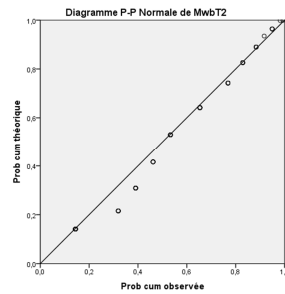
Kurtosis = -.78)



Perceived well-being

(Skewness = .81;

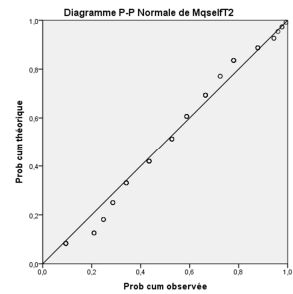
Kurtosis = .43)



Quantified-self

(Skewness = .12;

Kurtosis = -.97)



Word-of-mouth intentions

(Skewness = .45;

Kurtosis = -1.10)

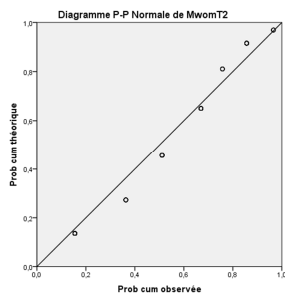


Table 88: Multivariate normality analysis (*Article 3; adoption of sleep apps*)

Appendix 4B: Moderating effects

Moderator	Effect	S.E.	t	LLCI	ULCI	ΔR^2	F	Hypothesis
BEFORE USE								
Privacy concerns								
H1: Use -> WoM								Supported
-1 S.D.	.53	.09	7.68***	.54	.92			
Mean	.46	.07	8.30***	.52	.83	1%	27.23***	
+1 S.D.	.38	.10	8.80***	.41	.84			
H2: IU -> Use								Supported
-1 S.D.	.67	.09	8.45***	.68	1.05			
Mean	.63	.06	7.91***	.67	.93	1%	51.02***	
+1 S.D.	.59	.08	8.34***	.55	.90			
H3: PU -> IU								Not supported
-1 S.D.	.66	.10	5.30***	.35	.77			
Mean	.68	.07	8.87***	.53	.83	0%	27.58***	
+1 S.D.	.68	.10	7.48***	.59	1.02			
H4a: PEU-> PU								Not supported
-1 S.D.	.23	.14	1.63*	-.05	.52			
Mean	.14	.10	2.06*	-.01	.40	0%	1.20ns	
+1 S.D.	.15	.15	1.01*	-.14	.45			
H4b: PEU -> IU								Not supported
-1 S.D.	.11	.14	.78ns	-.17	.39			
Mean	.15	.10	1.49ns	-.04	.37	1%	1.06ns	
+1 S.D.	.22	.15	1.46ns	-.07	.52			
Well-being personality								
H5a: Perceived well-being -> PEU								Not supported
-1 S.D.	.28	.14	1.01*	-.14	.44			
Mean	.28	.10	1.69*	-.06	.35	1%	.83ns	
+1 S.D.	.28	.16	1.83*	-.19	.47			
H5b: Perceived well-being -> PU								Supported
-1 S.D.	.19	.11	2.46***	.38	.82			
Mean	.22	.08	2.00***	.51	.83	1%	23.43***	
+1 S.D.	.25	.12	2.84***	.48	.98			
H5c: Perceived well-being -> IU								Supported
-1 S.D.	.00	.12	.37*	.16	.65			
Mean	.02	.08	.19*	.40	.75			
+1 S.D.	.13	.13	5.33***	.46	1.01	2%	14.56***	

Moderator	Effect	S.E.	t	LLCI	ULCI	ΔR^2	F	Hypothesis	
H5e: Perceived well-being -> WoM									
	-1 S.D.	.12	.11	2.17***	.26	.73		Supported	
	Mean	.17	.08	1.87***	.43	.77	1%		16.25***
	+1 S.D.	.20	.13	2.20***	.43	.97			
Empowered personality									
H6a: Quantified-self -> Perceived well-being									
	-1 S.D.	.85	.09	7.89***	.54	.90		Supported	
	Mean	.79	.06	12.03***	.65	.92	1%		49.19***
	+1 S.D.	.72	.08	9.72***	.68	1.03			
H6b: Quantified-self -> PU									
	-1 S.D.	.56	.10	5.52***	.56	.96		Not supported	
	Mean	.56	.07	5.04***	.59	.88	0%		35.07***
	+1 S.D.	.52	.09	6.45***	.53	.91			
H6c: Quantified-self -> PEU									
	-1 S.D.	-.09	.14	-1.62ns	-.38	.20		Not supported	
	Mean	-.18	.10	-1.08ns	-.16	.25	0%		.96ns
	+1 S.D.	.04	.14	1.27ns	-.10	.46			
H6d: Quantified-self -> IU									
	-1 S.D.	.33	.11	4.82*	.32	.77		Supported	
	Mean	.31	.08	2.21*	.48	.80	1%		21.63***
	+1 S.D.	.27	.10	6.74*	.52	.95			
H6f: Quantified-self -> WoM									
	-1 S.D.	.23	.11	6.73***	.31	.77		Supported	
	Mean	.19	.08	7.55***	.46	.79	1%		20.09***
	+1 S.D.	.14	.11	6.33***	.48	.92			
AFTER USE									
Privacy concerns									
H1: Use -> WoM									
	-1 S.D.	.50	.09	9.09***	.64	1.01		Not supported	
	Mean	.49	.07	8.30***	.77	1.05	0%		54.56***
	+1 S.D.	.49	.10	9.17***	.78	1.21			
H2: IU -> Use									
	-1 S.D.	.59	.09	10.19***	.58	.95		Supported	
	Mean	.56	.06	10.34***	.59	.85	1%		33.05***
	+1 S.D.	.52	.09	10.07***	.48	.86			
H3: PU -> IU									
	-1 S.D.	.73	.13	12.38***	.59	1.14		Not supported	
	Mean	.74	.08	14.88***	.71	1.06	0%		36.00***
	+1 S.D.	.79	.12	13.30***	.66	1.16			

Moderator	Effect	S.E.	t	LLCI	ULCI	ΔR^2	F	Hypothesis
H4a: PEU-> PU								
-1 S.D.	.10	.09	2.27**	.02	.38			Not supported
Mean	.09	.06	1.98**	.06	.34	0%	57.01***	
+1 S.D.	.09	.10	1.91**	-.01	.42			
H4bc: PEU -> IU								
-1 S.D.	.21	.11	1.86**	-.01	.43			Not supported
Mean	.21	.08	2.09**	.01	.34	0%	2.09ns	
+1 S.D.	.14	.13	1.07ns	-.12	.41			
Well-being personality								
H5a: Perceived well-being -> PEU								
-1 S.D.	.27	.11	3.55***	-.11	.36			Not supported
Mean	.29	.08	4.07***	-.05	.29	0%	.85ns	
+1 S.D.	.29	.13	4.10***	-.15	.38			
H5b: Perceived well-being -> PU								
-1 S.D.	.28	.10	4.46***	.37	.80			Supported
Mean	.31	.07	4.04***	.50	.81	1%	23.81***	
+1 S.D.	.33	.12	5.95***	.48	.97			
H5c: Perceived well-being -> IU								
-1 S.D.	.13	.11	3.36**	.16	.62			Supported
Mean	.20	.08	2.05***	.38	.72	2%	14.67***	
+1 S.D.	.26	.13	2.06***	.45	.98			
H5d: Perceived well-being -> Use								
-1 S.D.	.08	.11	4.07***	.23	.67			Supported
Mean	.10	.08	6.47***	.36	.67	1%	14.09***	
+1 S.D.	.12	.12	4.66***	.33	.83			
H5e: Perceived well-being -> WoM								
-1 S.D.	.10	.09	7.18***	.20	.58			Supported
Mean	.13	.06	7.87***	.34	.62	1%	16.66***	
+1 S.D.	.15	.10	8.31***	.35	.78			
Empowered personality								
H6a: Quantified-self -> Perceived well-being								
-1 S.D.	.78	.05	13.41***	.66	.90			Supported
Mean	.82	.04	19.95***	.74	.91	1%	67.03***	
+1 S.D.	.87	.05	15.36***	.76	.98			
H6b: Quantified-self -> PU								
-1 S.D.	.31	.06	4.85***	.69	.95			Not supported
Mean	.31	.04	4.04***	.70	.88	0%	50.44***	
+1 S.D.	.33	.06	4.16***	.63	.88			

Moderator	Effect	S.E.	t	LLCI	ULCI	ΔR^2	F	Hypothesis
H6c: Quantified-self -> PEU								Not supported
-1 S.D.	.25	.10	2.55**	.05	.45			
Mean	.30	.07	4.21***	.16	.44	0%	6.14***	
+1 S.D.	.34	.09	3.52**	.15	.53			
H6d: Quantified-self -> IU								Supported
-1 S.D.	.17	.07	8.18**	.47	.78			
Mean	.20	.05	2.42**	.57	.78	1%	26.04***	
+1 S.D.	.22	.07	9.74**	.58	.87			
H6e: Quantified-self -> Use								Supported
-1 S.D.	.22	.07	4.08****	.57	.85			
Mean	.26	.05	3.58***	.63	.83	1%	35.61***	
+1 S.D.	.28	.06	3.94***	.62	.89			
H6f: Quantified-self -> WoM								Not supported
-1 S.D.	.28	.06	7.63***	.65	.92			
Mean	.28	.04	7.96***	.67	.86	0%	42.48***	
+1 S.D.	.24	.06	8.37***	.61	.87			

*** indicates p -value < .001; ** p -value < .01; * p -value < .1; IU stands for intention of use; PU for perceived usefulness; PEU for perceived ease of use; WoM for word-of-mouth.

Table 89: Details of the moderating effects (Article 3; adoption of sleep apps)

Appendix 5: Article 4 (*The acceptance process of the Internet of Things: How to improve the acceptance of the IoT technology?*)

Appendix 5A: Multivariate normality analysis

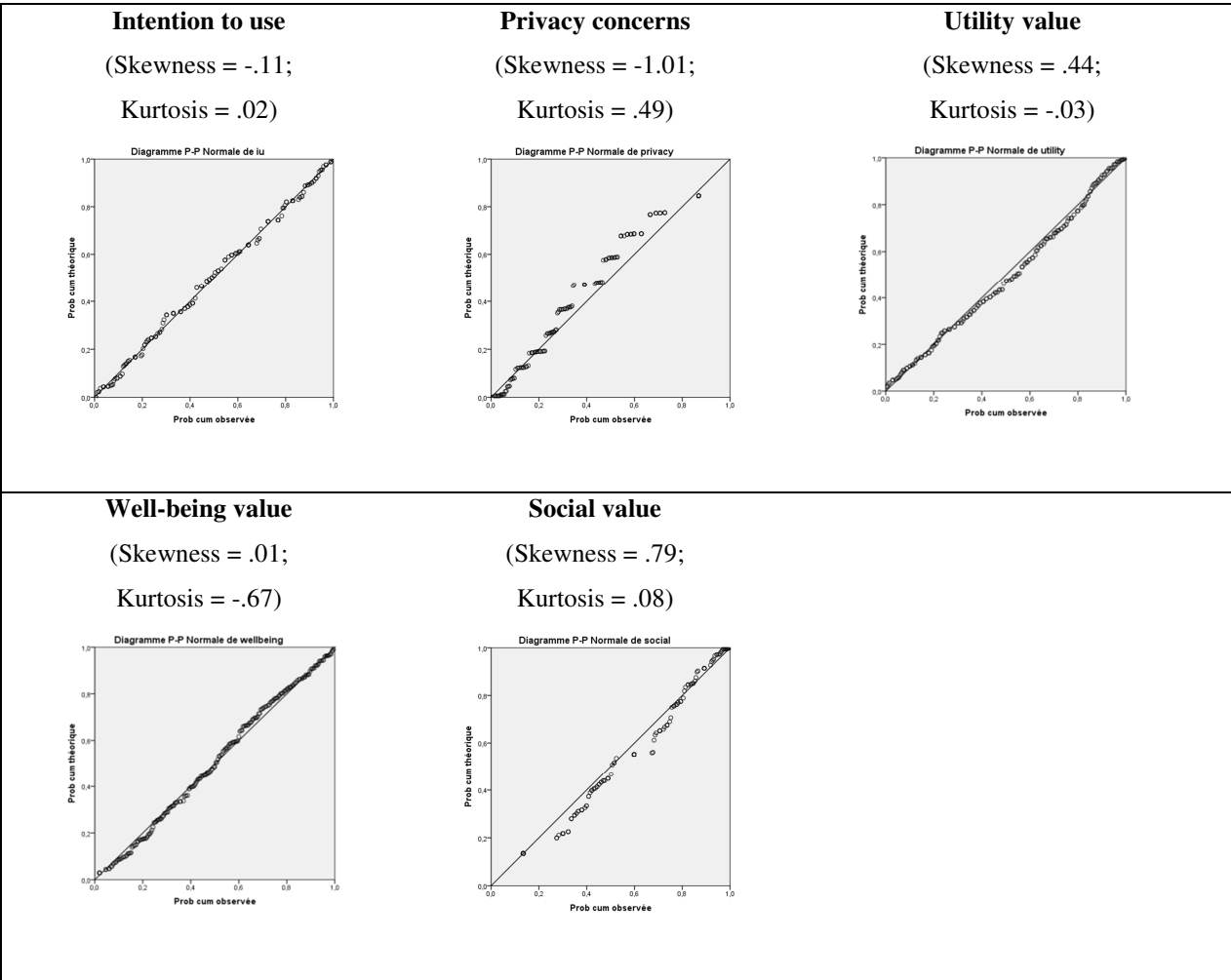


Table 90: Multivariate analysis (*Article 4; acceptance of smart homes*)

Appendix 5B: Moderating effects

Moderator	Effect	S.E.	t	LLCI	ULCI	ΔR^2	F	Hypothesis
Innovativeness								
H1a: Privacy concerns -> IU								Not supported
-1 S.D.	-.23	.11	6.18***	.61	.62			
Mean	-.21	.12	6.55***	.55	-.81	0%	2.31ns	
+1 S.D.	-.20	.13	6.80***	.42	-.07			
H2: Utility value -> IU								Supported
-1 S.D.	.28	.10	3.35***	.70	.80			
Mean	.35	.11	3.44***	.64	.73	2%	10.21***	
+1 S.D.	.38	.11	3.24***	.44	.80			
H3: Well-being value -> IU								Supported
-1 S.D.	.38	.14	3.32***	.45	.78			
Mean	.41	.17	3.23***	.33	.63	1%	12.31***	
+1 S.D.	.45	.18	3.48***	.61	.72			
H4a: Social value -> IU								Supported
-1 S.D.	.21	.11	5.34***	.35	.50			
Mean	.23	.12	5.56***	.61	.35	1%	11.19***	
+1 S.D.	.25	.13	5.01***	.44	.55			

*** indicates p -value < .001; ** p -value < .01; * p -value < .1; IU stands for intention of use.

Table 91: Details of the moderating effects (Article 4; acceptance of smart homes)

Appendix 6: Article 5 (*Consumers' acceptance and resistance factors toward smart connected stores*)

Appendix 6A: Multivariate normality analysis

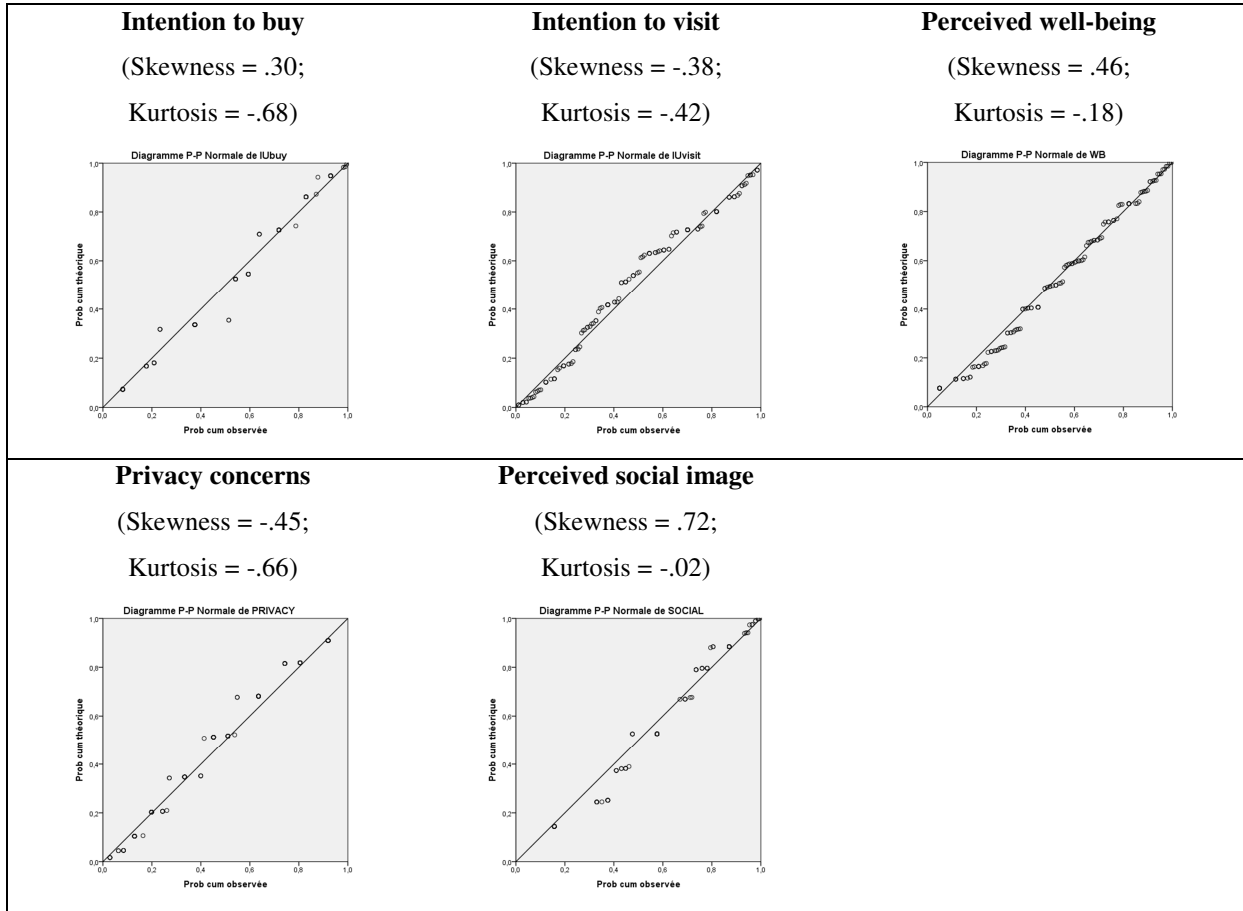


Table 92: Multivariate analysis (*Article 5; acceptance of smart stores*)

Appendix 6B: Moderating effects

Moderator	Effect	S.E.	t	LLCI	ULCI	ΔR^2	F	Hypothesis
Innovativeness								
H1: Intention to visit -> Intention to buy								Supported
-1 S.D.	.55	.10	10.35***	.62	.72			
Mean	.66	.11	11.03***	.56	.57	1%	2.31ns	
+1 S.D.	.72	.13	11.45***	.61	.61			
H2: Privacy concerns -> Intention to visit								Not supported
-1 S.D.	-.24	.07	-4.81***	.66	-.19			
Mean	-.26	.11	-4.69***	.08	.33	0%	2.81ns	
+1 S.D.	-.23	.04	-4.44***	.31	.44			
H4: Well-being -> Intention to visit								Not supported
-1 S.D.	.22	.10	4.31**	.43	.18			
Mean	.22	.16	3.45***	.88	-.33	0%	3.51*	
+1 S.D.	.25	.02	3.11***	.71	-.77			
H6: Perceived social image -> Intention to visit								Not supported
-1 S.D.	.11	.08	1.33**	-.44	.51			
Mean	.10	.12	1.89**	-.41	.55	0%	4.50ns	
+1 S.D.	.10	.12	1.45**	-.47	.55			
Well-being personality								
H1: Intention to visit -> Intention to buy								Supported
-1 S.D.	.68	.09	11.19***	-.31	-.56			
Mean	.66	.10	11.03***	-.35	-.61	1%	11.23***	
+1 S.D.	.62	.10	10.99***	-.33	-.57			
H2: Privacy concerns -> Intention to visit								Supported
-1 S.D.	-.19	.12	-4.75***	-.77	-.38			
Mean	-.26	.13	-4.69***	-.74	-.33	1%	12.23***	
+1 S.D.	-.28	.17	-4.43***	-.72	-.34			
H4: Well-being -> Intention to visit								Supported
-1 S.D.	.29	.13	3.47***	-.65	-.48			
Mean	.22	.15	3.45***	-.62	-.44	1%	10.24***	
+1 S.D.	.19	.15	3.39***	-.61	-.42			
H6: Perceived social image -> Intention to visit								Supported
-1 S.D.	.14	.11	2.33**	-.44	-.51			
Mean	.10	.11	1.89**	-.41	-.55			
+1 S.D.	.07	.12	1.85**	-.43	-.55	1%	12.16***	

Moderator	Effect	S.E.	t	LLCI	ULCI	ΔR^2	F	Hypothesis
Empowered personality								
H1: Intention to visit -> Intention to buy								Supported
-1 S.D.	.61	.10	11.17***	.56	.77			
Mean	.66	.12	11.03***	.45	.79	1%	10.22***	
+1 S.D.	.72	.11	11.83***	.44	.83			
H2: Privacy concerns -> Intention to visit								Supported
-1 S.D.	-.28	.13	-4.67***	.66	.72			
Mean	-.26	.15	-4.69***	.62	.65	3%	9.35***	
+1 S.D.	-.12	.17	-4.63***	.55	.66			
H4: Well-being -> Intention to visit								Not supported
-1 S.D.	.22	.08	3.48***	.33	.42			
Mean	.22	.12	3.45***	-.87	.76	0%	10.67*	
+1 S.D.	.21	.04	3.47***	2.38	1.34			
H6: Perceived social image -> Intention to visit								Not supported
-1 S.D.	.10	.03	1.47*	.63	-.56			
Mean	.10	.09	1.89**	1.29	-.87	0%	10.13***	
+1 S.D.	.16	.10	2.59**	.98	.31			

*** indicates p -value < .001; ** p -value < .01; * p -value < .1.

Table 93: Details of the moderating effects (*Article 5; acceptance of smart stores*)

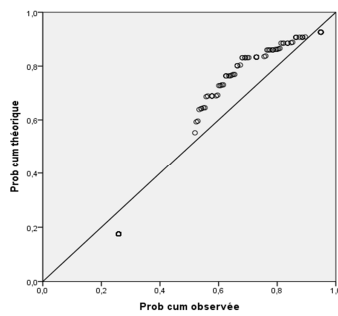
Appendix 7: Article 6 (*How do smart connected objects improve consumer well-being over time?*)

Appendix 7A: Multivariate normality analysis

EARLY ADOPTERS

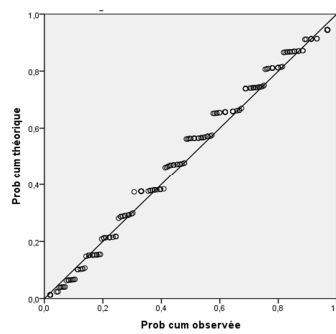
Real use

(Skewness = $-.24$;
Kurtosis = -1.77)



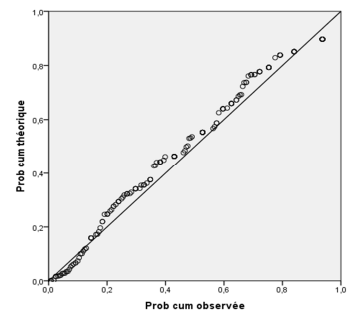
Perceived usefulness

(Skewness = $-.37$;
Kurtosis = $-.54$)



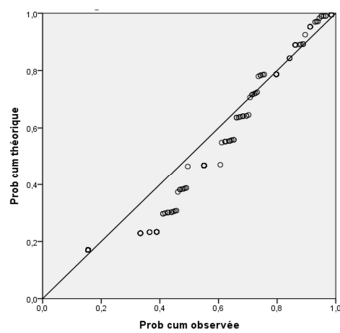
Perceived ease of use

(Skewness = $-.86$;
Kurtosis = $.66$)



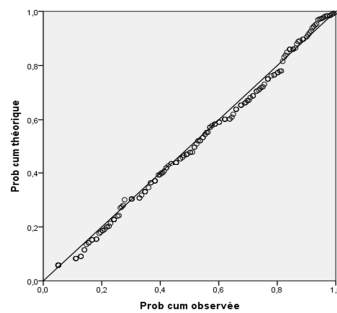
Perceived social image

(Skewness = $.93$;
Kurtosis = $-.04$)



Perceived well-being

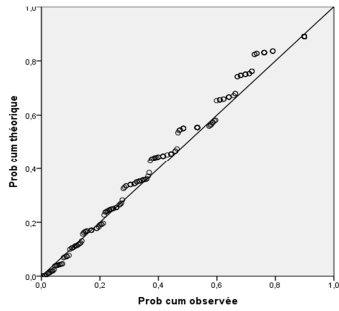
(Skewness = $.32$;
Kurtosis = $-.36$)



EARLY MAJORITY

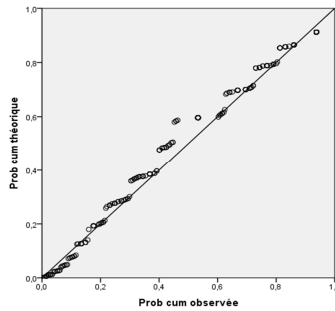
Real use

(Skewness = $-.65$;
Kurtosis = $.02$)



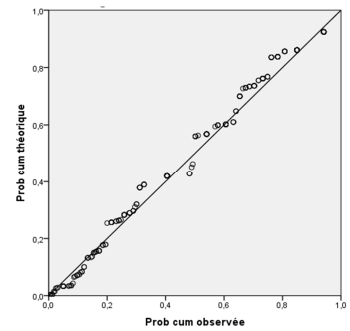
Perceived usefulness

(Skewness = $-.67$;
Kurtosis = $-.01$)



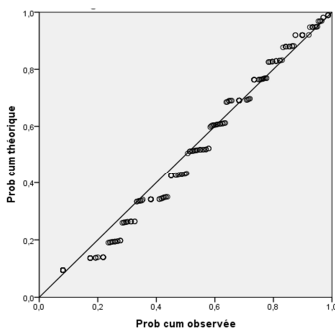
Perceived ease of use

(Skewness = $-.46$;
Kurtosis = $-.33$)



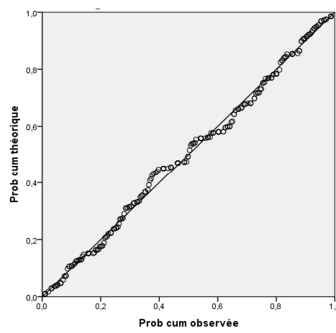
Perceived social image

(Skewness = $.93$;
Kurtosis = $-.04$)



Perceived well-being

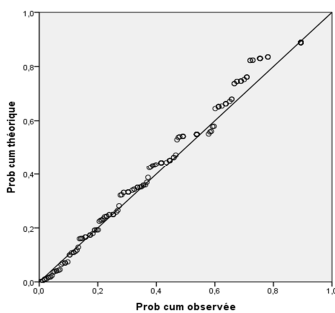
(Skewness = $-.01$;
Kurtosis = $-.24$)



LATE MAJORITY

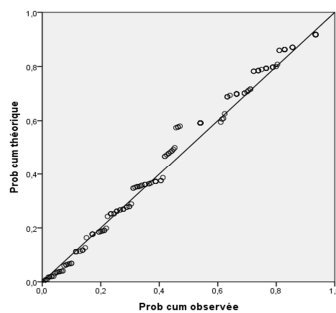
Real use

(Skewness = $-.62$;
Kurtosis = $-.03$)



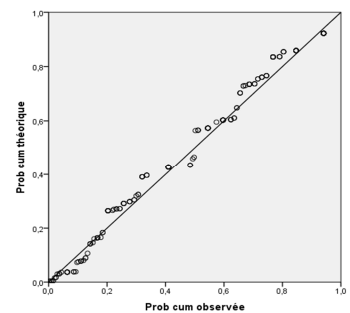
Perceived usefulness

(Skewness = $-.51$;
Kurtosis = $-.25$)



Perceived ease of use

(Skewness = $-.49$;
Kurtosis = $-.30$)



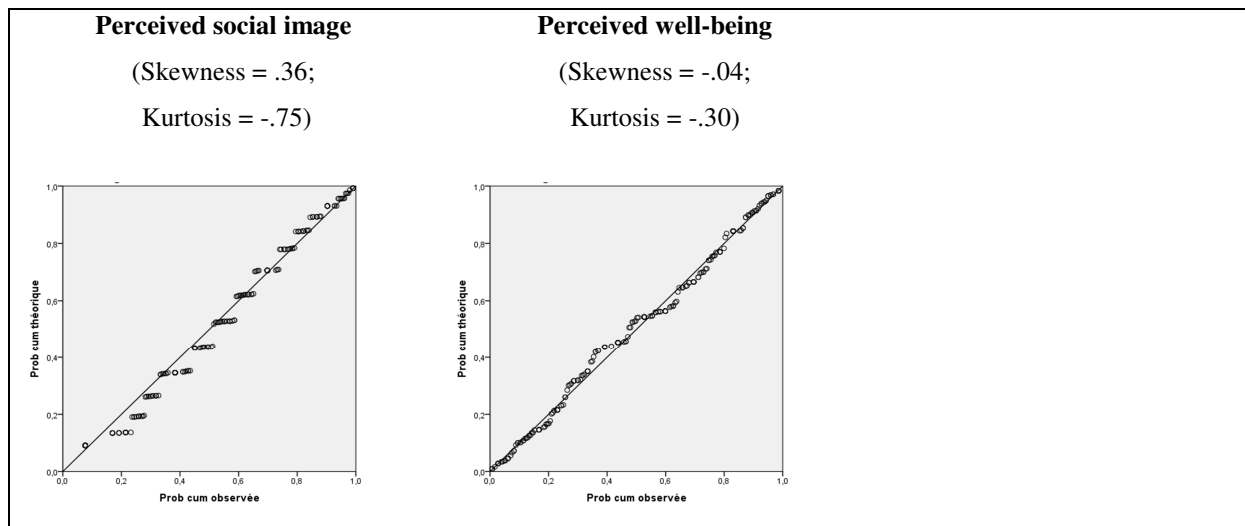


Table 94: Multivariate normality analysis (*Article 6; influence of SCO on well-being*)

Appendix 7B: Moderating effects

Moderator	Effect	S.E.	t	LLCI	ULCI	ΔR ²	F	Hypothesis
EARLY ADOPTERS								
Privacy concerns								
H5: PU -> real use								Not supported
-1 S.D.	.22	.09	3.31*	.23	.33			
Mean	.23	.07	2.07*	.34	-.31	0%	2.55ns	
+1 S.D.	.23	.07	4.42*	.31	-.48			
H6: PEU -> real use								Supported
-1 S.D.	.23	.10	3.87*	.20	.56			
Mean	.19	.11	2.03*	.28	.50	1%	10.22***	
+1 S.D.	.15	.11	2.89*	.26	.52			
H8: PEU -> PU								Supported
-1 S.D.	.53	.12	7.67***	.62	.67			
Mean	.49	.10	6.69***	.57	.68	1%	11.21***	
+1 S.D.	.37	.11	8.01***	.66	.73			
Innovativeness								
H5: PU -> real use								Not supported
-1 S.D.	.23	.09	3.31*	.25	.27			
Mean	.23	.07	2.07*	.34	-.31	0%	21.33*	
+1 S.D.	.23	.07	4.42*	.31	-.48			
H6: PEU -> real use								Not supported
-1 S.D.	.22	.07	3.87*	.32	.57			
Mean	.19	.06	2.03*	-.30	.71	0%	23.33***	
+1 S.D.	.20	.08	2.89*	.42	-.62			
H8: PEU -> PU								Supported
-1 S.D.	.42	.11	7.19***	.34	.62			
Mean	.49	.12	6.69***	.32	.67	1%	17.66***	
+1 S.D.	.56	.14	8.23***	.30	.80			
EARLY MAJORITY								
Privacy concerns								
H5: PU -> real use								Not supported
-1 S.D.	.14	.06	3.21*	.36	.62			
Mean	.14	.05	2.11*	.46	.66	0%	47.37***	
+1 S.D.	.13	.07	2.33*	.49	.78			

Moderator	Effect	S.E.	t	LLCI	ULCI	AR ²	F	Hypothesis
H6: PEU -> real use								
	-1 S.D.	.18	.07	3.92***	.28	.56		Not supported
	Mean	.18	.05	3.02***	.31	.53	0% 20.59***	
	+1 S.D.	.17	.07	4.61***	.27	.58		
H8: PEU -> PU								
	-1 S.D.	.48	.06	10.90***	.42	.66		Not supported
	Mean	.48	.04	10.32***	.49	.69	0% 47.55***	
	+1 S.D.	.48	.06	10.23***	.50	.77		
Innovativeness								
H5: PU -> real use								
	-1 S.D.	.10	.06	3.21**	.40	.66		Supported
	Mean	.14	.05	3.13**	.44	.65	1% 41.10***	
	+1 S.D.	.18	.07	3.43**	.41	.71		
H6: PEU -> real use								
	-1 S.D.	.15	.07	3.92***	.23	.52		Supported
	Mean	.18	.06	3.02***	.31	.54	3% 20.13***	
	+1 S.D.	.22	.08	4.61***	.31	.63		
H8: PEU -> PU								
	-1 S.D.	.44	.07	10.90***	.30	.57		Supported
	Mean	.48	.05	10.32***	.42	.63	1% 35.50***	
	+1 S.D.	.56	.07	10.23***	.47	.77		
LATE MAJORITY								
Privacy concerns								
H5: PU -> real use								
	-1 S.D.	-.02	.07	2.68*	.29	.60		Supported
	Mean	-.06	.05	2.23*	.40	.63		
	+1 S.D.	-.09	.08	2.25*	.43	.76	1% 27.68***	
H6: PEU -> real use								
	-1 S.D.	.36	.07	5.22***	.25	.57		Supported
	Mean	.33	.06	4.10***	.27	.51	1% 13.89***	
	+1 S.D.	.31	.08	4.25***	.20	.54		
H8: PEU -> PU								
	-1 S.D.	.50	.07	9.98***	.35	-.64		Not supported
	Mean	.50	.05	9.19***	.45	.67	0% 34.46***	
	+1 S.D.	.59	.07	9.25***	.49	.78		

Moderator	Effect	S.E.	t	LLCI	ULCI	ΔR ²	F	Hypothesis
Innovativeness								
H5: PU -> real use								Supported
-1 S.D.	-.08	.07	2.68*	.30	.61			
Mean	-.06	.05	2.23*	.39	.62	1%	28.06***	
+1 S.D.	.12	.08	2.25*	.38	.71			
H6: PEU -> real use								Supported
-1 S.D.	.28	.08	3.34***	.11	.45			
Mean	.33	.06	4.10***	.25	.52	1%	14.12***	
+1 S.D.	.49	.09	5.50***	.32	.67			
H8: PEU -> PU								Not supported
-1 S.D.	.50	.07	9.98***	.25	.56			
Mean	.50	.06	9.19***	.42	.67	0%	31.86***	
+1 S.D.	.50	.08	8.29***	.52	.85			

*** indicates p -value < .001; ** p -value < .01; * p -value < .1; PU stands for perceived usefulness; PEU for perceived ease of use.

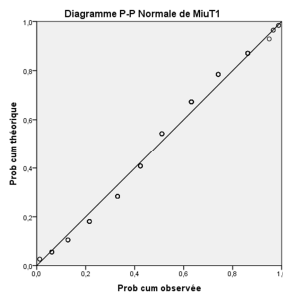
Table 95: Details of the moderating effects (Article 6; influence of SCO on well-being)

Appendix 8A: Multivariate normality analysis

BEFORE USE

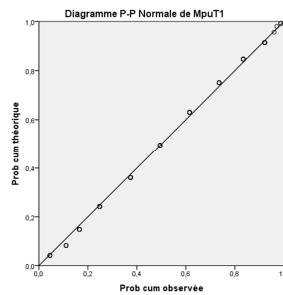
Intention to use

(Skewness = $-.02$;
Kurtosis = $-.84$)



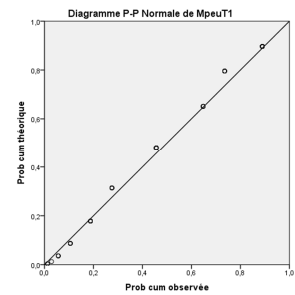
Perceived usefulness

(Skewness = $.08$;
Kurtosis = $-.45$)



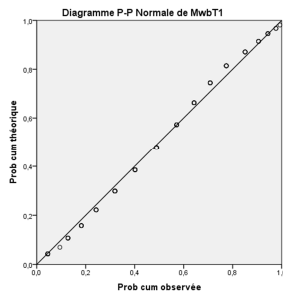
Perceived ease of use

(Skewness = $-.54$;
Kurtosis = $.15$)



Perceived well-being

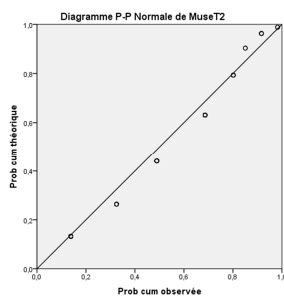
(Skewness = $.01$;
Kurtosis = $-.85$)



AFTER USE

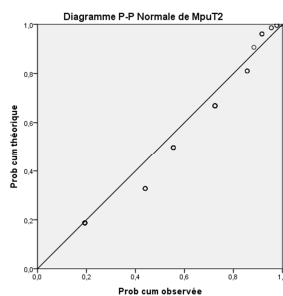
Use

(Skewness = $.67$;
Kurtosis = $-.46$)



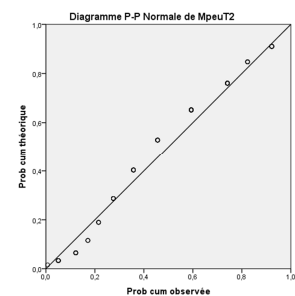
Perceived usefulness

(Skewness = 1.26 ;
Kurtosis = 1.37)



Perceived ease of use

(Skewness = $-.45$;
Kurtosis = $-.78$)



Perceived well-being

(Skewness = .81; Kurtosis = .43)

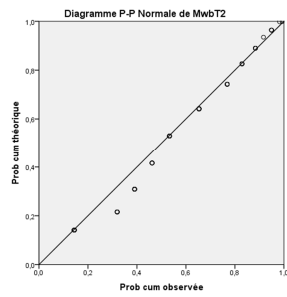


Table 96: Multivariate analysis (*Article 7; influence of sleep apps on well-being*)

Appendix 8B: Moderating effects

Moderator	Effect	S.E.	t	LLCI	ULCI	ΔR^2	F	Hypothesis
BEFORE USE								
Well-being personality								
H1: PEU -> Perceived well-being								Not supported
-1 S.D.	.02	.09	.99ns	.45	.54			
Mean	.01	.04	.12ns	-.48	-.67	0%	31.22***	
+1 S.D.	.02	.08	.44ns	-.71	.98			
H3: PU -> Perceived well-being								Supported
-1 S.D.	.49	.17	5.18***	.54	1.22			
Mean	.54	.09	5.15***	.66	1.03	1%	37.15***	
+1 S.D.	.61	.09	5.66***	.62	1.01			
Privacy concerns								
H1: PEU -> Perceived well-being								Not supported
-1 S.D.	.04	.12	.27ns	.33	.17			
Mean	.01	.13	.12ns	.34	.04	0%	4.56ns	
+1 S.D.	.08	.11	.33ns	.49	.02			
H3: PU -> Perceived well-being								Supported
-1 S.D.	.48	.11	6.67***	.26	.32			
Mean	.54	.12	5.15***	.24	.35	2%	33.18***	
+1 S.D.	.59	.11	5.01***	.27	.27			
AFTER USE								
Well-being personality								
H1: PEU -> Perceived well-being								Not supported
-1 S.D.	.02	.08	.35ns	-.84	.45			
Mean	.04	.06	.63ns	-.65	.69	0%	3.44ns	
+1 S.D.	.01	.04	.33ns	-.75	.59			
H2: Real use -> Perceived well-being								Not supported
-1 S.D.	.41	.18	3.43**	.44	.10			
Mean	.41	.17	2.76**	.54	.07	0%	11.23**	
+1 S.D.	.42	.15	2.35**	.42	.17			
H3: PU -> Perceived well-being								Not supported
-1 S.D.	.43	.09	3.49***	1.29	.42			
Mean	.43	.10	3.39***	-.98	.42			
+1 S.D.	.41	.11	4.33***	.87	.46	0%	10.28**	

Moderator	Effect	S.E.	t	LLCI	ULCI	ΔR^2	F	Hypothesis
Privacy concerns								
H1: PEU -> Perceived well-being								Not supported
-1 S.D.	.03	.09	.32ns	-.84	.45			
Mean	.04	.07	.63ns	-.65	.69	0%	45.44*	
+1 S.D.	.04	.05	.34ns	-.75	.59			
H2: Real use -> Perceived well-being								Not supported
-1 S.D.	.42	.18	3.43**	.44	.10			
Mean	.41	.17	2.76**	.54	.07	0%	36.12*	
+1 S.D.	.41	.15	2.35**	.42	.17			
H3: PU -> Perceived well-being								Not supported
-1 S.D.	.43	.09	3.49***	1.29	.42			
Mean	.43	.10	3.39***	-.98	.42	0%	33.45**	
+1 S.D.	.42	.12	4.34***	.87	.46			

*** indicates p -value < .001; ** p -value < .01; * p -value < .1; PU stands for perceived usefulness; PEU for perceived ease of use.

Table 97: Details of the moderating effects (Article 7; influence of sleep apps on well-being)

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Abstract

Over the last decade, technological and Internet innovations have increasingly invaded the consumer market (N'Goala, 2016). The Internet of Things (IoT) is becoming a common platform, and disrupts relationships between consumers and companies (Bohli et al., 2009); in essence, this is a timely research. The major goal of this thesis is to deepen the understanding of the acceptance and the adoption processes of the IoT and smart connected technologies, as well as the related consequences on perceived well-being. To do this, four contexts of study have been explored: smart connected objects, smart sleep applications, smart homes, and smart stores. First, we performed qualitative exploratory studies, and secondly we conducted quantitative studies to build conceptual models according to our qualitative findings and the literature. The results show that technology benefits are the first factors that enable technology acceptance through perceived usefulness and perceived ease of use; subsequently, self-improvement, through perceived social image and well-being benefits, are the main reasons to continue using the IoT and smart connected technologies. The acceptance and the adoption of these technologies also depend on users' personality traits while perceived risks and fears on the use of the personal data are the main barriers. In turn, the IoT and smart connected technologies influence perceived well-being according to the experience of use, personality traits, and the technology.

Keywords: Internet of Things; new technology acceptance; consumer well-being; privacy concerns; social value; utility value.

Mots clés : Internet des objets ; acceptation des nouvelles technologies ; bien-être du consommateur ; préoccupations liées à la vie privée ; valeur sociale ; valeur utilitaire.