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Understanding Acceptance of eHealthcare by IoT Natives and IoT Immigrants: An Integrated Model of UTAUT, Perceived Risk, and Financial Cost

Running title: Integrated Model for eHealthcare Acceptance

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Abstract

The Internet of Things (IoT) is a modern disruptive technological approach that connects devices and people in a smart way at any time and at any place. The development of IoT is forecast to generate high economic value, improve efficiency of enterprises' operational processes, and benefit the personal and professional lives of its end users. This new model of human–technology interaction is under-researched, especially with regard to eHealth. The current study aims to close this research gap by investigating IoT adoption in eHealthcare from the customer perspective and by including financial cost in the extended Unified Theory of Acceptance and Use of Technology (UTAUT) framework. The model is validated based on data collected from a randomly selected sample of 268 potential users of IoT-based healthcare devices in France. Structural modelling reveals that the cost of using IoT in eHealthcare is the key barrier to IoT adoption. Age is a significant mediator of customers' intention to use IoT in eHealthcare and inspires the formulation of two new categories: IoT natives and IoT immigrants. The findings have practical application for IoT developers, policymakers, and potentially for marketers.

Keywords: IoT adoption, eHealthcare, extended UTAUT model, generation gap, IoT native, IoT immigrant.

1. Introduction

Changes in social and economic systems generated by the rapid development of new technologies have driven a global revolution, which has become known as the 4th Industrial Revolution. Industry 4.0 manifests with the rapid development of the Internet of Things (IoT), artificial intelligence, and machine learning; it is radically changing human lifestyles and contributing significantly to the development of new production methods. Healthcare 4.0 is one of the main domains of the 4th Industrial Revolution, using various Industry 4.0 concepts in healthcare (Kumar et al., 2020). Industry 4.0 is completely revolutionizing eHealth and its whole ecosystem (Aceto et al., 2020). This study focuses on one of the most important drivers of the 4th Industrial Revolution, namely, the IoT, and sheds light on its importance in eHealthcare. Specifically, we investigate IoT adoption in eHealthcare from the customer perspective and by considering the key determinants for its adoption.

The IoT is a concept of a worldwide network composed of any object (thing) that can be embedded into any environment with the aim of measuring variables (physical, electrical, etc.) and sending this information through the Internet to some other location for storage and/or analysis (Dijkman et al., 2015; Metallo et al., 2018). “Things” in the IoT concept are a new dimension of existing human and application interaction, which enable people and objects to be connected and exchange information in real time. The interconnected device networks can lead to a large number of smart and autonomous applications and services that can bring significant personal, professional, and economic benefits (Almobaideen et al., 2017).

IoT is developing at a tremendous pace in the world. According to the “Fortune Business Insight” study, the global IoT market was estimated at US\$190 billion in 2018 and is expected to reach US\$1102.6 billion by 2026. Another recent study, “Networked World: Risks and Opportunities in the Internet of Things” conducted by the insurance company Lloyd's, indicates that there will be more than 20 billion connected objects in the world by 2025. This revenue forecast encompasses the full breadth of the IoT ecosystem, including smart and

embedded systems shipments, connectivity services, infrastructure, purpose-built IoT platforms, applications, security, analytics, and professional services (Nord et al., 2019).

eHealthcare is one of topics involving IoT with the most potential, being one of the main sectors in which the IoT could have the most relevant economic and social impacts (Martínez-Caro et al., 2018). Recently, a large number of significant technological improvements in both hardware and software components have been required to develop consistent, safe, effective, timely, flexible, patient-centered, and power-efficient healthcare systems (Bhattacharya, 2017; Gao and Bai, 2014; Martínez-Caro et al., 2018).

Healthcare has a clear opportunity today to seize the benefits of IoT technology. Healthcare and medical applications at home and in hospitals have become “early-bird applications of the IoT” (Su et al., 2011). The market size of IoT use in healthcare is expected to grow from US\$55,5 billion in 2019 to US\$188,0 billion by 2024¹. eHealthcare refers to services in healthcare using the Internet and includes the use of such technologies as connected devices, computers, mobile phones, websites, and applications (Lepore et al., 2018; Pagliari et al., 2005). eHealthcare is one of the areas of IoT application with the most relevant economic and social impacts (Martínez-Caro et al., 2018). Laplante and Laplante (2016) discuss potential applications of IoT in the healthcare industry that include, for example, distant monitoring of patients with eating disorders, and detecting exercise abuse during training. Hoque (2016) proves that mHealth can reduce cost, save time, provide better access, and increase the interaction between patients, nurses, and doctors as well as provide a faster means to send messages about diseases and health.

At the same time, the concept of IoT raises a lot of concern and therefore, opens new avenues for research. This study identifies a gap in the research on exploring the influence of such variables as financial cost on IoT adoption in healthcare. The reason for this gap is that a lot of research is performed from organizations’ perspective, not customers’ perspective. For example, Wu et al. (2011) study mobile healthcare adoption in hospitals; Chong et al. (2015) investigate radio frequency identification (RFID) adoption by physicians and nurses, that is, people who do not pay for their use of the IoT product. Furthermore, many previous studies have focused on adoption predictors (e.g., e-skills and e-loyalty) but only a few have investigated the barriers to eHealth adoption.

It is widely accepted that the ability to adopt technological innovation and digital behavior differs depending on customers’ age, that is, their membership of a particular generation (Dharmesti, 2019; Lissitsa and Kol, 2016). Currently, only a few researchers have investigated the influence of the generational variable on eHealth adoption. The present study aims to close this gap by deepening knowledge about IoT acceptance in eHealth among different age groups.

Therefore, the key research question of this study is: what are the perceived barriers to IoT adoption in healthcare? The UTAUT model is used as a theoretical basis for the research; we extend it by including perceived risk and financial cost variables, with age and gender as moderators. The study provides a customer view on acceptance of IoT-based connected devices.

The remainder of this paper is organized as follows. Section 2 provides a literature review on general research about IoT adoption with emphasis on non-traditional approaches and new models. Section 3 presents the conceptual framework. In Subsection 3.1, various extensions

¹https://www.businesswire.com/news/home/20200103005328/en/?fbclid=IwAR2YGITNdMRUxtqN_rOFJdo6dxLo8fgGzyZPbt77gFXHl6zank1JFfuxM70

of the UTAUT model are benchmarked in relation to the healthcare industry and mobile banking. A detailed summary of empirical and theory-based research using the UTAUT and UTAUT2 models is provided. In Subsection 3.2, the conceptual model developed in this study is explained and the hypotheses are formulated. In Section 4, the methodology is, and data collection are described. The data are analyzed in Section 5. Section 6 discusses the results. The final section concludes.

2. Literature Review: Key Directions of IoT Adoption Research

In the academic literature, quantitative research on IoT adoption exists but is not abundant. While studying IoT adoption, researchers most often refer to the technology acceptance model (TAM), UTAUT model, and task-technology fit model (Yang et al., 2013). Usually, these models perform quite well, however, some limitations have been revealed. For example, Gao and Bai (2014) reveal that the traditional acceptance models can be enriched by additional characteristics, such as fun and pleasure; trust is proved to affect perceived usefulness of IoT technology. Kim et al. (2017) make another attempt to enrich the TAM by combining it with the value-based adoption model (VAM). The authors study customers' adoption of smart home service. The VAM operates with benefits (usefulness and enjoyment, variety seeking) and sacrifice (technicality and perceived fee). These factors are considered to be influencers of perceived value and therefore, of customers' motivation for using a technology.

A novel way of investigating IoT adoption is provided in Hsu and Lin (2016). Consumers' motivation for using IoT has been researched from the perspective of network externalities and information privacy concerns. Network externalities are defined as the value or effect that users obtain from a product or service will bring about more value to consumers with the increase of users, complementary products, or services" (Katz and Shapiro, 1985). Perceived benefits have been proved to play a key role in explaining users' behavior with regard to IoT services. Perceived compatibility as well as perceived critical mass significantly influence the perceived benefits. It has also been revealed that information privacy concerns have less effect on consumers' intention to use IoT relative to perceived benefits.

Hoffman and Novak (2017) explore IoT adoption, and state that "human-centric conceptualization of consumer experience as consumers' internal subjective responses to branded objects may not be sufficient to conceptualize consumer experience in the IoT" (p.1178). The unique features of IoT objects interact with customers and produce unique experiences and meanings for each customer, who combines (or assembles) smart objects in a different way to another. With the aim of providing a deeper understanding of consumer experience, the authors build a conceptual framework based on DeLanda's assemblage theory, which unites consumer experience and object experience.

Caputo et al. (2018) investigate the relationships among the elements that affect customers' motivations and decisions to use IoT-based products by using motivation theories. For their model, they choose the following factors: extrinsic motivators (entertainment, social interaction) and intrinsic factors (e.g., information acquisition, privacy risk, and technology readiness level). They reveal that entertainment as well as social interactions and information acquisition and technology readiness are positive predictors of customers' motivation for using IoT products.

The study by Kim (2016) stands out for its use of a psychological and user-experience approach to investigate human-IoT interactions. The goal of the study is to reveal which factors make the IoT experience more valuable for customers. The author draws on the computers are social actors paradigm and the modality, agency, interactivity, and navigability model of technology effects and formulates the research question and asks whether IoT

devices can be perceived as technological sources, not only as communication channels. The results of the research reveal that source attribution (i.e., using information from one source or from several sources) plays an important role in determining the quality of human–IoT interaction. The study proves that psychological factors are very influential as technological components of IoT.

Jayashankar et al. (2018) research IoT adoption in agriculture among US farmers based on the consumption value theory. In their model, the authors consider that risk and value affect IoT adoption and examine how trust affects perceived value and risk. They find that trust enhances perceived value and negatively affects perceived risk. Furthermore, perceived risk of personal data being misused can negatively influence IoT adoption.

In summary, the literature review reveals that nowadays, research on IoT adoption has developed in two major ways: (1) searching for new ways to improve the traditional models and (2) developing novel approaches based on consumer psychology, human–technology interaction, conceptualizing the notion of customer experience, and more. However, traditional models still dominate the research landscape. The most newly developed extended models include perceived usefulness and perceived ease of use from TAM; trust, awareness, privacy concern, and attitude are also common variables discussed; by comparison, cost and prices are rarely included in the models.

Research on IoT adoption in healthcare is rather scarce. One of the earlier quantitative works investigating new technology acceptance in healthcare services is Hu et al. (1999). At the time of their research, IT infrastructure was rather primitive, technology was immature, etc. Hu et al. (1999) is one of the first attempts to embrace user technology acceptance literature and telemedicine research and management needs in one study. Their study validates the existing IT acceptance/adoption literature (TAM and theory of planned behavior, TPB) and examines physician acceptance of telemedicine technology. It confirms that perceived ease of use (PEOU) has positive effects on both attitude and perceived usefulness. However, neither of these is statistically significant; PEOU has no significant effect on attitude; and thus, the limitations of the TAM model are revealed. Wu et al. (2011) research adoption of mobile healthcare in hospitals by integrating the TAM and TPB. Chong et al. (2015) study RFID adoption by physicians and nurses. The authors extend the traditional UTAUT with individual characteristics of people (neuroticism, conscientiousness, openness to experience, etc.) and demographic characteristics. The study proves that personality traits are among the most important predictors of RFID adoption. Younger physicians and nurses adopt RFID more easily. It is interesting to note that personality and demographic characteristics are stronger predictors of RFID adoption than UTAUT variables are.

Martínez-Caro et al. (2018) research how healthcare services are moving toward the IoT era. The authors investigate the reasons for comparatively low IoT adoption in healthcare from the end-user perspective based on Seddon's (1997) information system success model, which includes measures of information and system quality, measures of perceived usefulness and perceived satisfaction, and other measures of net benefits of information systems use. The authors add e-skills of users and e-loyalty to the model. They prove that user satisfaction leads to e-loyalty, and user satisfaction is conditioned by perceived usefulness. In addition, perceived usefulness is based on personal innovativeness, e-skills, and self-efficacy.

After reviewing studies on IoT adoption in eHealth, we reach the following conclusions. a) The research domain is emerging and there are many research gaps. b) Researchers usually consider the problem from an organizational perspective and therefore, miss important issues of eHealth adoption, such as price and gender. Only a few studies (e.g., Karahoca et al., 2018; Martinez-Caro et al., 2018) embrace the customer-centered approach. c) Researchers rarely

investigate the role of age in eHealth adoption (one of the rare studies that unites the customer perspective with the age variable is Sivathanu (2018) on IoT-based adoption of wearables by elderly people). Finally, d) at present, the UTAUT model is considered to be the most suitable for studying eHealth adoption; however, there is a need to improve it. These research gaps inspire the current study. In the following section, we reflect further on eHealth adoption processes and discuss the evolution of the UTAUT model, explaining why it is the most suitable for the current research. The new conceptual framework for this study is developed and the research hypotheses formulated.

3. Conceptual Framework

3.1. Extended Unified Theory of Acceptance and Use of Technology for IoT in eHealthcare

To understand technology adoption, Venkatesh et al. (2003) empirically compare eight competing models: the theory of reasoned theory, TAM and TAM2, TPB and DTPB, combined TAM and TPB, IDT, motivational model, model of PC utilization, and social cognitive theory. They survey 215 respondents from four organizations. From their longitudinal studies, Venkatesh et al. (2003) combine and elaborate on these eight models and develop a new one, called the UTAUT.

The UTAUT model not only highlights the core determinants predicting intention to adopt, but also enables researchers to analyze the contingencies of moderators that would increase or decrease the effects of those determinants. Since the UTAUT model has been empirically validated and shown to be superior to other models (Park et al., 2007; Venkatesh and Zhang, 2010; Venkatesh et al., 2003), this study employs it as the theoretical framework for the development of our hypotheses.

The UTAUT model has four fundamental constructs (i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions) that influence behavioral intention to use a technology and/or technology use. We adapt these constructs and definitions from the UTAUT model to the consumer technology acceptance and use context. According to the UTAUT model, performance expectancy, effort expectancy, and social influence are theorized to influence behavioral intention to use a technology, while behavioral intention and facilitating conditions determine technology use. The UTAUT model was first developed to study the adoption of technologies in the workplace. It was then extended to explore the factors that influence the adoption of innovations at the individual level in different contexts (Venkatesh et al., 2012). For example, the UTAUT model has been used to identify the factors influencing the decision to adopt online family dispute resolution services (Casey and Wilson-Evered, 2012), electronic tax filing (Carter et al., 2011), and health information technology (Kijisanayotin et al., 2009). Therefore, the UTAUT model is generally extended by additional contextual constructs that incorporate specific factors from the use domain (Venkatesh et al., 2012; Kijisanayotin et al., 2009), such as the doctor–patient relationship (Liu et al., 2013), or social capital factors, including social trust, institutional trust, and social participation (Tsai, 2014). The introduction of additional contextual predictors enables a more refined understanding of user acceptance of the technology, which is always field specific (Holden and Karsh, 2010; Venkatesh et al., 2012). Since its inception, the UTAUT model has been widely used in the field of technology research on adoption and diffusion as a theoretical focus by researchers investigating empirical studies on user intention and behavior. In the same line, Williams et al. (2015) report that the UTAUT model has successfully harmonized the technology adoption literature.

Moreover, the complexity of health systems is derived from, among others, patients and their health conditions, providers and the interactions among them, and the work processes within and across settings (Kuziemsky and Ghazzawi, 2019).

The UTAUT model seems to be relevant in our research based on its validity in previous studies, since the variables of the initial model have been confirmed for the health context (Kijasanayotin et al., 2009). In addition, several authors have found limited use of the UTAUT model in the fields of journalism, psychology, education, and medicine. They suggest extending the UTAUT to additional and diverse fields of study that are neglected and require much attention (Williams et al., 2015). However, analysis of the UTAUT model recognized in the different studies shows that focusing on a single issue, such as community, culture, country, organization, agency, department, person, or age group, is the most common limitation. In this study, we aim to overcome these limitations.

As recommended by Cimperman et al. (2016), since the UTAUT model was originally used to measure the acceptance of technology in an organizational environment, the consumer perspective and the healthcare context, in the current study, have to be considered when adapting the measurement scales. In addition, since the current study is specific to the IoT for eHealthcare, we should consider extended specific constructs in the research model. For instance, financial constraints and perceived risk factors may influence consumers' willingness to adopt IoT for monitoring their health condition.

3.2. Conceptual Model and Formulation of Hypotheses

To empirically test the relationships between performance expectancy, effort expectancy, social influence, facilitating conditions, perceived risk and financial cost and their influence on behavioral intention toward the IoT for eHealth, a conceptual model is developed based on the UTAUT model outlined in the literature review. In this conceptualized model, the performance expectancy, effort expectancy, social influence, facilitating conditions, perceived risk, and financial cost are the predictors of intention to use connected healthcare devices, while age and gender are moderators. Intention to use connected healthcare devices is the only outcome variable. Figure 1 illustrates this conceptual research model. Hypothetical relationships between the research constructs are then tested and discussed.

The dependent variable in this study is **behavioral intention (BI)**, which refers to the degree to which a technology or any connected object or device is intended to be used by consumers. Venkatesh et al. (2003) empirically validate the UTAUT model for various business areas, including the public sector, telecommunications services, finance, and entertainment. The model has also been useful for studying the organizational acceptance of new information technologies. The present study explores the impact of consumers' perceived ease of use, usefulness, and perceived risk on behavioral intention toward IoT for eHealth.

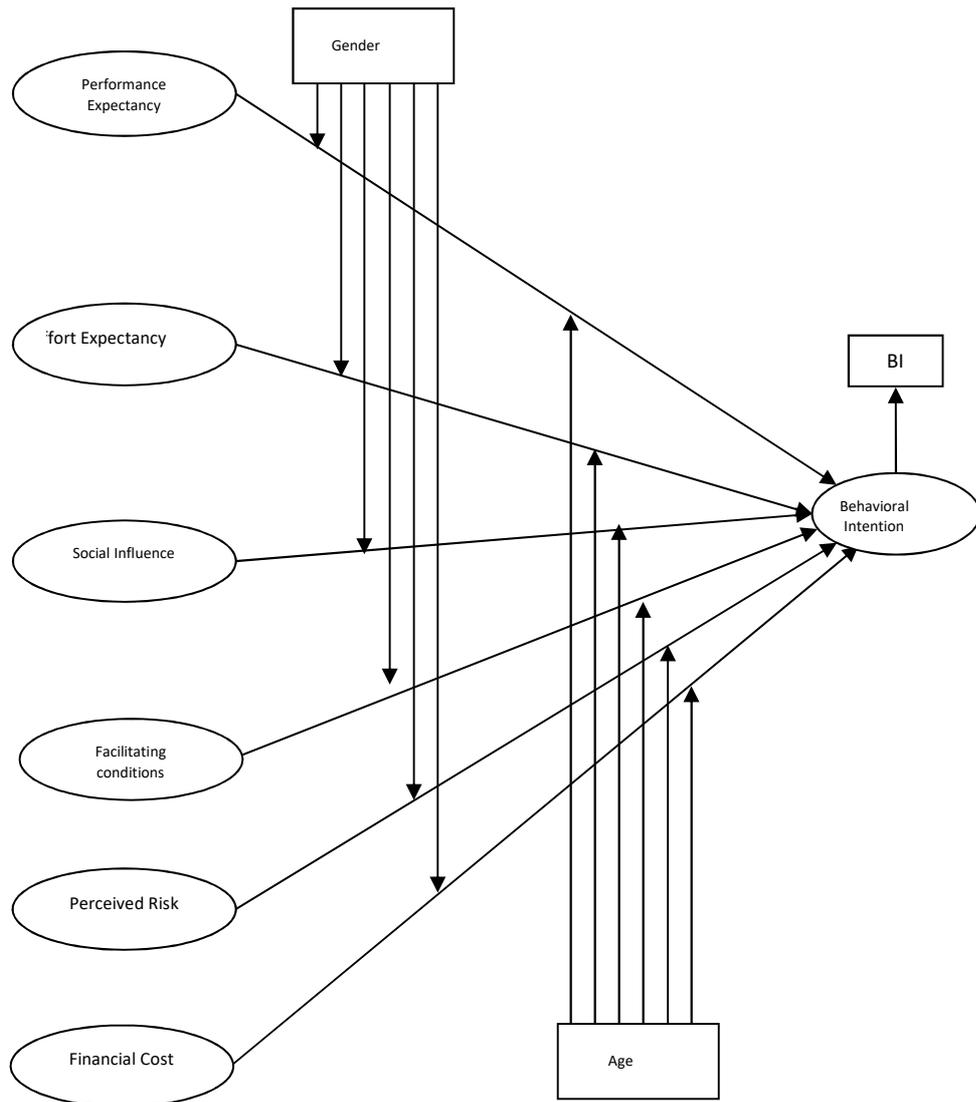


Figure 1. Conceptual Model

Performance expectancy (PE) is defined as the degree to which adopting a technology brings effectiveness to users in performing certain activities (Venkatesh et al., 2003, 2012). In the context of wearable medical devices, effectiveness can be viewed as the extent to which the device can assist consumers in monitoring daily physical conditions, making self-care plans and minimizing threats to one’s health. Thus, PE refers to the extent to which one believes that the system will enhance the healthcare experience of end users. An increase in the PE of connected healthcare devices by end users, such as the perception of more effective management of their health, better access to healthcare services, and better overall quality of life, has a positive effect on the ease of use of connected healthcare devices by end users (Hoque and Sorwar, 2017). Therefore, we can hypothesize as follows.

H1: Performance expectancy positively impacts intention to use healthcare devices by the end-users.

Effort expectancy (EE) refers to the “the degree of ease associated with using the system” (Venkatesh et al., 2003, p. 450). In the initial use of a technology especially, such as the acceptance of an innovation, the level of ease associated with using that technology strongly affects the acceptance behavior (Cimperman et al., 2016). Accordingly, the degree to which

users perceive a technology as being easy to use influences their perception of the utility of the technology, making effort expectancy the precursor to perceived usefulness (Pal et al., 2018). Furthermore, in the context of use of connected healthcare devices by end users, effort expectancy is associated with an increase in the perception of a technology as being more beneficial and useful. As a result, higher effort expectancy refers to the energy required to manage the system (Or et al., 2011). Thus, we formulate the following hypothesis.

H2: Effort expectancy negatively impacts intention to use healthcare devices by the end-users.

Social influence (SI) is defined as the degree to which an individual perceives the importance of the views of peers regarding whether they should use the new system (Venkatesh et al., 2003). Literature predicting patient behavior in the acceptance of ICTs in healthcare has shown that social influence is a significant determinant, since the opinions of peers and colleagues have a strong influence on user behavior (Cimperman et al., 2016; Kijisanayotin et al., 2009). Some studies have highlighted the complex role of social influence in the acceptance of new technologies (Bhattacharjee and Hikmet, 2008; Mital et al., 2018; Sicari et al., 2015). We hypothesize as follows.

H3: Social Influence positively impacts the intention to use healthcare devices by the end-users.

Facilitating conditions (FC) refer to the availability of technological resources and technical infrastructure. Several studies have investigated the impact of facilitating conditions on consumers' perceived ease of use (Jahangir and Begum, 2008; Mital et al., 2018; Sicari et al., 2015). Facilitating conditions may positively influence consumers' perceived ease of use of connected devices. Moreover, previous studies have highlighted the connection between the availability of technological resources and technical infrastructure, and their perceived usefulness. The authors of these studies argue that there is a positive connection between the perceived usefulness of using connected devices and associated facilitating conditions (Bhattacharjee and Hikmet, 2008; Heinz et al., 2013). Thus, the following hypothesis is proposed.

H4: Facilitating conditions positively influence the intention to use healthcare devices by the end-users.

Perceived risk (PR) refers to an individual's perception about the potential outcomes of an action owing to his or her degree of uncertainty about a particular behavior. The reason for this is that people want to avoid losses as much as possible when making decisions in risky situations, which can be achieved through certain actions. The literature initially defined perceived risk only in terms of fraud or product quality, but today, the definition has shifted to the potential for loss in the pursuit of the desired outcome when using an e-service (Featherman and Pavlou, 2003). A considerable number of works have demonstrated how the perceived risks of using connected devices are likely to influence decision making and ultimately behavioral intentions (Benson et al., 2015; George, 2004; Ha and Stoel, 2009; Hansen et al., 2004; Liu et al., 2005; Saridakis et al., 2015). Many studies have found that any increase in a consumer's perceived risk can negatively influence the consumer's behavioral intention. Accordingly, users of connected devices with high-risk propensity are less likely to be interested in healthcare connected devices. Thus, the following hypothesis is formulated.

H5: Perceived risk negatively influences consumers' behavioral intention to use healthcare devices.

Financial cost (FC) refers to the price value that is the cognitive trade-off of consumers between the perceived benefits of using mobile services and the monetary cost of using those services (Venkatesh et al., 2012). It includes such items as the costs of data service operators (mobile Internet), the costs of purchasing the device, and service charges where applicable. Previous studies have reported that perceived financial cost is a barrier to the use and adoption of mobile services (Ali et al., 2017; Hanafizadeh et al., 2014; Teerapat et al., 2013). Recently, several authors have highlighted that as the IoT is a new concept for consumers, they face many difficulties regarding the adoption of IoT products/services (Li and Deng, 2020). Thus, potential users who do not know what value the IoT can bring them might not be willing to pay high prices and might perceive financial cost as a barrier. This study hypothesizes as follows.

H6: Financial cost negatively influences consumers' behavioral intention to use healthcare devices.

The age variable acts as a moderator in the current study, drawing from the notion of “generation” in the work of Mannheim (1952), which gave rise to the famous generational theory (GT). Initially, Strauss and Howe (1991) put forward the idea that people from a certain age group are inclined to share a certain set of beliefs, values, and patterns of behavior, because they grew up in the same historical eras. Later, in the mid-1990s, organizations became aware that GT could help them to resolve their strategic problems, as it aided understanding not only of people’s life trajectories, but also their consumer behavior (Parment, 2013), ability to adopt innovations, and digital behavior (Dharmesti et al, 2019; Lichy, 2016; Lissitsa and Kol, 2016).

Howe and Strauss’ (2000) book, *Millennials Rising: The Next Great Generation*, discusses the tremendous change in attitudes and values across generations. The categorization of the birth dates for generations varies from one study to another; however in most studies the following six main generations are identified: GI Generation (1901–1924), Silent Generation (1925–1942), Baby Boomers (1943–1960), Gen X (1961–1981), Gen Y (1982–1998), and Gen Z (1999–2019) (Lichy, 2016).

This generational classification is in line with the literature on the generational differences in the use of IT and the adoption of technology innovations (Brenngman et al., 2005; Chak and Leung, 2004; Geissler et al., 2006; Venkatesh et al., 2012). For example, Brenngman et al. (2005) find that age is a key determinant of e-retail shopping adoption by consumers both in the US and Belgium. Geissler et al. (2006) assert that the generations aged 35 years and under comprise the highest Internet usage group. Chak and Leung (2004), studying the influences of age on Internet addiction, find that full-time students are more likely to be addicted to the Internet. Venkatesh et al. (2003, 2012) point out the psychological foundations of the moderating role of age in the relationship between performance expectancy, effort expectancy, social influence, and facilitating conditions and the behavioral intentions of the consumer. Based on the findings of Jennings and Jacoby (1993) and Morris et al. (2005), they argue that older people tend to rely largely on automatic information processing (Hasher and Zacks, 1979) and have difficulties in processing new information even for new technologies. This conditions their effort and the performance they expect from the usage of a new technological environment as the eHealthcare environment. It also increases the importance of the facilitating conditions in the behavioral intention of the user. Indeed, because of their increasing cognitive and physical limitations, older people rely more than younger ones on facilitating conditions to determine their intention to adopt eHealthcare. Furthermore, as demonstrated by Rhodes (1983) (in Venkatesh et al., 2003), social pressure increases with age

as the affiliation needs increase. These likely conditions the intention of older people (more than younger people) to adopt innovation because of social modeling and influence.

Furthermore, according to Venkatesh et al. (2003, 2012), the effects of the UTAUT variables on behavioral intention differ between genders. These authors find that men, because they are highly task oriented (Minton and Schneider, 1980) focus almost entirely on performance expectancy to determine their behavioral intention and more so than women. By comparison, women give importance to effort expectancy, social influence, and facilitating conditions to define their behavioral intention. Women are less task oriented than man (Lynott and McCandless, 2000), are more sensitive to other opinions, and place greater emphasis on external supporting factors (Venkatesh and Davis, 2000). We hypothesize as follows.

H7: Age and gender moderate the effects of performance expectancy, effort expectancy, social influence, and facilitating conditions on consumers' behavioral intention.

Hypotheses	
H1	Performance expectancy positively impacts intention to use healthcare devices by the end-users.
H2	Effort expectancy negatively impacts intention to use healthcare devices by the end-users.
H3	Social Influence positively impacts the intention to use healthcare devices by the end-users.
H4	Facilitating conditions positively influence the intention to use healthcare devices by the end-users.
H5	Perceived risk positively influences the intention to use healthcare devices by the end-users.
H6	Financial cost negatively influences consumers' behavioral intention to use healthcare devices.
H7	Age and gender moderate the effects of performance expectancy, effort expectancy, social influence, and facilitating conditions on consumers' behavioral intention.

Table 1. Research Hypotheses

4. Methodology

4.1. Data Collection and Sample Description

Data are collected through an anonymous online survey developed and operated via the web platform Qualtrics. The main focus of the survey is to collect data on the IoT users' behavioral intention in eHealth. The survey looks to measure the main determinants of users' behavioral intention toward IoT in eHealth. These determinants are IoT users' performance expectancy, effort expectancy, financial cost of the connected object, users' perceived risk, social influence for adopting IoT, and facilitating conditions toward the adoption of IoT. The references and properties of the measure scales are discussed in Section 5. Moreover, to be sure that the respondents possess the same understanding of the IoT healthcare product, a summarized definition of the IoT healthcare product is provided at the beginning of the survey. Then, the respondents are asked if they are familiar with IoT healthcare products or not. If the answer is yes, they are asked to complete the survey. If the answer is no, they end participation in the survey.

The target population is French men and women aged between 16 and 65 years. The questionnaire received 268 responses, of which 60 indicated that they did not use IoT-based devices (wearables, medical devices, etc.) and consequently, were removed from the sample. We also checked for incomplete answers and any dubious responses to the initial open questions, which resulted in removing 27 responses from the sample. This left the study with a total of 181 responses for analysis.

More than 50% of the sample is represented by those aged younger than or between 16 and 20 years and 23% by those aged between 20 and 30 years. However, the gender representativity of the survey goes through a distribution of relative female frequency of 63% and relative male frequency of 37%. Concerning marital status, more than 60% of the sample comprises singles and roughly 30% are engaged to be married. Table 1 summarizes the basic demographic characteristic of the sample. The distribution of the sample with respect to socio-professional status shows that it is composed of mainly students (39%), employees (29%), and executives and intellectual professionals. Table 2 presents the relative and individual frequency of each demographic characteristic of the sample.

Variables	Categories	Frequency per category	Relative frequency per category (%)
A. Age (years)	<20	98	54
	[21–30]	41	23
	[31–40]	9	5
	[41–50]	5	3
	[51–60]	26	14
	> 60	2	1
B. Gender	Male	67	37
	Female	114	63
Marital status	Single	116	64
	Engaged	65	36
Socio-professional status	1. Farmer	4	2
	2. Artisans, shopkeepers, CEOs	5	3
	3. Executives and intellectual professionals	34	19
	4. Intermediate professions	4	2
	5. Employees	52	29
	6. Workers	3	2
	7. Retired	3	2
	8. Unemployed	6	3
	9. Students	70	39

Table 2. Sample Demographic Characteristics

4.2. Accuracy of the Measure Scales

To ensure the content validity of the measured variables, the used measurement scales are adapted from previous studies and reworded to the specific context of IoT adoption (Table 3). The measure of the constructs is adapted from referred studies with some adaptation to the context of IoT healthcare products (refer to Table A.1). The measures of performance expectancy, effort expectancy, social influence, and facilitating conditions are adapted from the UTAUT measures proposed Venkatesh et al. (2003). Their statistical properties are confirmed by Foon and Fah (2011), Sripalawat et al. (2011), and Venkatesh and Zhang (2010). Perceived risk and financial cost are adapted from Stone and Gronhaug (1993) for the former and Luarn and Lin (2005) for the latter. Their validity and reliability are confirmed by Laroche et al. (2004) for the first and Sripalawat et al. (2011) for the second.

Behavioral intention is evaluated by a single-item measure adapted from the measure of Venkatesh and Zhang (2010). The usage of the single-item measure of behavioral intention is

based on the recommendations of Bergkvist and Rossiter (2007), who assert that the use of a single item is suitable for measures in which the multiple items representing the attribute (in the answer part of the item) are synonyms or intended synonyms, which is the case of the original three-item measures of BI presented by Venkatesh et al. (2003): “*I intend to use the system in the next <n> months*”; “*I predict I would use the system in the next <n> months*”; and “*I plan to use the system in the next <n> months.*” Moreover, the choice of the single-item measure of BI is in line with Rossiter (2002), who argues that “a single-item measure is sufficient if the construct is such that in the minds of respondents: (1) the object of the construct is “concrete singular,” meaning that it consists of one object that is easily and uniformly imagined, and (2) the attribute of the construct is “concrete,” again meaning that it is easily and uniformly imagined.” In other words, with reference to its definition as a representation of the user intention and willingness to use the system, behavioral intention is a construct in which the object and the attribute are concrete and uniformly imagined in the minds of raters.

Variables	Number of items	Developed by	Adapted by
Performance Expectancy	4	Venkatesh et al. (2003)	Foon and Fah (2011), Venkatesh and Zhang (2010)
Effort expectancy	4	Venkatesh et al. (2003)	Foon and Fah (2011), Sripalawat et al. (2011), Venkatesh and Zhang (2010)
Social Influence	3	Venkatesh et al. (2003)	Foon and Fah (2011), Venkatesh and Zhang (2010)
Perceived Risk	4	Stone and Gronhaug (1993)	
Facilitating Conditions	4	Venkatesh et al. (2003)	Foon and Fah (2011), Sripalawat et al. (2011), Venkatesh and Zhang (2010)
Financial Cost	3	Luarn and Lin (2005)	Sripalawat et al. (2011)
Behavioral Intention	1	Davis (1989)	Venkatesh and Zhang (2010), Venkatesh et al. (2003)

Table 3. References of the Measure Scales

The measurement model statistics are performed first by examining the reliability and the convergent and discriminant validity of the items and constructs. The reliability of the measures, as indicated by Cronbach’s alpha and Dillon and Goldstein’s rho, is satisfactory (Table 4). These indexes are higher than 0.7 and 0.8, respectively, for all the measures. For the convergent validity of the measures, the Rho of convergent validity, recommended by Fornell and Larcker (1981), is higher than 0.6 for all the scales. This result is consistent with the items’ loadings to their respective constructs, which are superior to 0.7, as recommended by Chin (1998) (Table 4). For the discriminant validity, all the items loadings are greater than 0.7, with no cross-loadings higher than 0.635 (Table A.2). In addition, the matrix of correlation between constructs indicates that the inter-construct correlations are less than the square-root of the average variance explained (Table 5).

Latent variable	Dimensions	Factor Loading	Cronbach's alpha	D.G. Rho (PCA)	LV Index Value	Rho of convergent validity	AVE
Performance Expectancy	PE1	0.870	0.896	0.928	3.960	0.761	0.761
	PE2	0.884					
	PE3	0.896					
	PE4	0.839					
Effort Expectancy	EE1	0.918	0.949	0.963	5.360	0.867	0.867
	EE2	0.940					
	EE3	0.934					
	EE4	0.932					
Social Influence	SI1	0.881	0.882	0.919	4.486	0.739	0.739
	SI2	0.896					
	SI3	0.812					
	SI4	0.846					
Facilitating Conditions	FC1	0.915	0.866	0.919	4.014	0.790	0.790
	FC2	0.924					
	FC3	0.825					
Perceived Risk	PR1	0.950	0.852	0.931	2.602	0.869	0.869
	PR2	0.914					
Financial Cost	FIC1	0.784	0.768	0.866	2.235	0.653	0.653
	FIC2	0.721					
	FIC3	0.909					
Behavioral Intention	BI	-	-	-	-	-	

Table 4. Accuracy Analysis Statistics

	Performance Expectancy	Effort Expectancy	Social Influence	Facilitating Conditions	Perceived Risk	Financial Cost
Performance Expectancy	0.761*					
Effort Expectancy	0.369	0.867*				
Social Influence	0.370	0.070	0.739*			
Facilitating Conditions	0.376	0.064	0.370	0.790*		
Perceived Risk	0.001	0.016	0.000	0.000	0.869*	
Financial Cost	0.002	0.027	0.006	0.004	0.021	0.653*
Behavioral Intention	0.501	0.403	0.190	0.195	0.012	0.041

* Average Variance Explained

Table 5. Discriminant Validity of the Structural Model

5. Empirical Results Analysis

In this study, a partial least square structural equation modeling (PLS-SEM) approach using xlstat-PLSPM software is used to test the research model and the related hypotheses. As supported by Hair et al. (2014), the partial least square approach is consistent for exploratory studies and a small sample size, because it does not require normal distribution of the

manifest variables. Furthermore, as mentioned by Mital et al. (2017), “it assumes that individual variables are changed one by one with the rest in the model and resultant model fit indices are monitored in the measurement part of the model.”

In addition, as recommended by Kwong and Wong (2013) and applied by Karahoca et al. (2018), the bootstrapping procedure is used to test the significance of the inner (measurement) and the outer (structural) model. This procedure calculates a bootstrap standard error and generates approximate t-values for significance testing of the structural path (Kwong and Wong, 2013).

5.1. Determinants of Intention Behavior of IoT Users

The results of the PLS-SEM show that the structural model has reliable properties (Table 6). The goodness-of-fit (GoF) index of the absolute model (GoF_AM= 0.679) is similar to the bootstrap estimates (GoF_AMb= 0.679), which means that the model has a satisfying GoF. The GoF of the outer (measurement) model is also high (GoF_OM= 0.993), confirming a satisfactory adjustment of the measurements for the seven variables. In addition, the goodness-of-fit index of the inner (structural) model is substantially high (GoF_IM= 0.905) and close to the bootstrap estimates of GoF (GoF_IMb= 0.943) indicating a good fit of the causal model to the empirical data (Table 6). These results are consistent with the coefficient determinant the R² value of 0.593, which is considered high in reference to Chin (1998). The R² value means that almost 60% of the variance of the behavioral intentions related to the IoT of consumers is explained by the considered independent variables (Table 7).

	GoF	GoF (Bootstrap)	Standard error
Absolute	0.679	0.679	0.043
Relative	0.898	0.922	0.050
Outer model	0.993	0.978	0.029
Inner model	0.905	0.943	0.046

Table 6. Goodness-of-Fit Index (Monofactorial Manifest Variables)

The test of the contributions of the independent variables to IoT users’ behavioral intention shows mixed results (Table 7). Users’ performance expectancy contributes positively to their behavioral intention. As Table 7 shows, the positive contribution is statistically significant ($w_i = 0.486$, T-stat= 6.329). The same positive contribution of consumers’ effort expectancy on their behavioral intention can be noted from Table 7. Its impact on behavioral intention is statistically significant ($w_i = 0.301$, T-stat = 4.705). However, as expected in theory, the IoT financial cost contributes negatively to users’ behavioral intention. The negative impact of the IoT financial cost is less important in magnitude than the positive impacts of performance expectancy and effort expectancy (-0.12 with a T-stat = -2.433 vs. 0.486 and 0.301). Moreover, the social influence on consumers’ adoption of IoT affects negatively users’ behavioral intention ($w_i = -0.288$, T-stat= -1.029), but unfortunately, its impact is statistically non-significant, as it’s the t-statistics show. The contributions of perceived risk and facilitating conditions on users’ behavioral intention are positive but non-significant at the statistical level.

In summary, following the empirical results presented in Table 6, we validate H1, H2, and H4. IoT performance expectancy positively influences consumers’ behavioral intention. IoT effort expectancy positively influences consumers’ behavioral intention. IoT financial cost negatively impacts users’ behavioral intention.

Dependent variable	Independent variable	Standardized path coefficient (coef. with bootstrap)	Standard error (coef. with bootstrap)	T (<1.65)	Pr > t (5% risk of error)	Bootstrap interval	
						Low limit (95%)	Upper limit (95%)
R ² =0.593 Adjusted R ² =0.581	Performance Expectancy	0.486 (0.477)	0.077 (0.090)	6.329	0.000	0.287	0.655
	Effort Expectancy	0.301 (0.313)	0.064 (0.067)	4.705	0.000	0.150	0.441
	Social Influence	-0.288 (-0.311)	0.280 (0.332)	-1.029	0.305	-1.269	0.286
	Facilitating Conditions	0.344 (0.365)	0.283 (0.348)	1.217	0.225	-0.246	1.356
	Perceived Risk	0.070 (0.067)	0.049 (0.040)	1.424	0.156	-0.010	0.147
	Financial Cost	- 0.120 (- 0.125)	0.049 (0.040)	- 2.433	0.016	-0.227	-0.031

Table 7. Results of the Test of the Contributions of the Independent Variables to Behavioral Intention

5.2. Moderation Effect of Gender

To test the moderation effect of gender on the links between the independent variables and the intention behavior, a multigroup comparison method, as recommended Chin and Dibbern (2010) is used. The moderating variables considered in the model are gender and age.

For the moderating effect of gender, causality is tested for the two groups, male respondents (67) and female respondents (114). The goodness-of-fit index of the resulting absolute models are close to each other (GoF_AM_{man}= 0.675; GoF_AM_{women}= 0.685) and are also close to the bootstrap estimates (GoF_AMb_{man}= 0.683; GoF_AMb_{women}= 0.696), which means that the two models have similar GoF. The GoF of the outer model is high (GoF_OM_{man}= 0.969; GoF_OM_{women}= 0.950), reflecting satisfactory adjustments of the measures of the variables. In addition, the GoF of the inner model is high for both groups (GoF_IM_{man}= 0.928; GoF_IM_{women}= 0.942), indicating that the causal model has a good fit to the empirical data (Table 8).

	Male			Female		
	GoF	GoF (Bootstrap)	Standard Error	GoF	GoF (Bootstrap)	Standard Error
Absolute	0.675	0.683	0.078	0.685	0.696	0.050
Relative	0.899	0.895	0.056	0.955	0.920	0.050
Outer Model	0.969	0.950	0.046	0.994	0.983	0.034
Inner Model	0.928	0.942	0.039	0.961	0.936	0.045

Table 8. Goodness-of-Fit Indexes of the Causal Models for Male and Female Groups

The results indicate a significant contribution of performance expectancy and effort expectancy to the intention behavior of male and female consumers related to IoT (Table 9). However, the results show a significant negative contribution of financial cost to behavior intentions for the female group ($w_i = -0.143$; $t = -2.200$) but not for the male group ($w_i = -0.036$; $t = -0.429$). This result means that women pay attention to financial cost when defining their

IoT behavioral intention. However, this finding cannot be confirmed, because the permutation test, which compares the statistics of the two subsamples and the original sample (Chin and Dibbern (2010); Jakobowicz, 2007), indicates that the difference between the path coefficients of this parameter does not differ significantly (Table 10). These results highlight that gender has no significant moderating effect in the impact of effort expectancy, performance expectancy, and financial cost on the IoT behavioral intentions of consumers.

Dependent variable	Independent variable	Standardized path coefficient (coef. with bootstrap)	Standard error (error value of bootstrap)	T (<1.65)	Pr > t (5% risk of error)	Bootstrap interval	
						Lower limit (95%)	Upper limit (95%)
Male R ² =0.624 Adjusted R ² =0.593	Performance Expectancy	0,618 (0,602)	0,123 (0,110)	5,014	0,000	0,354	0,808
	Effort Expectancy	0,277 (0,279)	0,100 (0,096)	2,765	0,008	0,105	0,489
	Social Influence	0,114 (0,044)	0,410 (1,034)	0,278	0,782	-1,530	1,185
	Financial Cost	-0,036 (0,012)	0,085 (0,126)	-0,429	0,669	-0,211	0,290
	Perceived Risk	0,092 (0,097)	0,083 (0,071)	1,108	0,272	-0,101	0,251
	Facilitating Conditions	-0,169 (-0,088)	0,416 (1,044)	-0,406	0,686	-1,251	1,432
Female R ² =0.594 Adjusted R ² =0.575	Performance Expectancy	0,422 (0,420)	0,101 (0,120)	4,161	0,000	0,209	0,663
	Effort Expectancy	0,303 (0,311)	0,086 (0,311)	3,540	0,001	0,070	0,484
	Social Influence	-0,519 (-0,503)	0,369 (0,437)	-1,407	0,162	-1,702	0,225
	Financial Cost	-0,143 (-0,137)	0,065 (0,085)	-2,200	0,030	-0,351	-0,021
	Perceived Risk	0,084 (0,085)	0,064 (0,061)	1,311	0,193	-0,175	0,216
	Facilitating Conditions	0,612 (0,599)	0,367 (0,433)	1,664	0,099	-0,212	1,760

Table 9. Test of the Moderation Effect of Gender on the Relationships of the Causal Model

Independent variables	Permutation test		
	Difference	P	Significance
Performance Expectancy	0,196	0,347	No
Effort Expectancy	0,027	0,881	No
Social Influence	0,633	0,386	No
Financial Cost	-0,179	0,158	No
Perceived Risk	0,008	0,891	No
Facilitating Conditions	0,781	0,317	No

Table 10. Test of Permutation

5.3. Moderation Effect of Age

As mentioned earlier, in most studies, six main generations are identified. In the current research, the last three generations are the most important because, these people are in the working place and are also proven users of digital technologies. These generations are Gen X (1961–1981), Gen Y (1982–1998), and Gen Z (1999–2019). Younger adults are more adept at using technologies while older adults are less skilled (Olson et al., 2011).

This study divides the sample into only two parts (older than 20 years old and younger than 20 years old) based on the fact that the term “Internet of Things” itself first appeared at the very end of the 1990s, when it was associated with RFID, and thus, the IoT is the same age as Gen Z.

To test the moderating effect of the age on the causal model, the sample of respondents is split into two groups: a group whose members are less than 20 years, and a group whose members are above 20 years. This choice of sampling enables us to examine the differences that could exist between Gen Z, born in the new century and considered as IoT natives, and the other generations, considered mostly as IoT immigrants.

For the moderating effect of age, the structural model is tested for the two groups, IoT natives (98 respondents) and IoT immigrants (83 respondents). The goodness-of-fit index of the absolute models of the IoT immigrants group is higher than that of the IoT natives’ group (GoF_AM_{natives}= 0.623; GoF_AM_{Immigrants}= 0.720) (Table 11). Nonetheless, their estimates are close to the bootstrap estimates (GoF_AMb_{natives}= 0.640; GoF_AMb_{Immigrants}= 0.731), which means that the two models have an acceptable GoF. Furthermore, the GoF of the outer model is high for both groups (GoF_OM_{natives}= 0.908; GoF_OM_{immigrants}= 0.992), reflecting a good fit of the model of measurement. In addition, the GoF of the inner model is high for both groups (GoF_IM_{natives}= 0.985; GoF_IM_{immigrants}= 0.976), indicating a good fit of the structural model.

	IoT Natives			IoT immigrants		
	GoF	GoF (Bootstrap)	Standard Error	GoF	GoF (Bootstrap)	Standard Error
Absolute	0.623	0.640	0.064	0.726	0.731	0.054
Relative	0.894	0.902	0.057	0.969	0.921	0.052
Outer Model	0.908	0.948	0.042	0.992	0.976	0.038
Inner Model	0.985	0.952	0.046	0.976	0.943	0.035

Table 11. Goodness-of-Fit Indexes of the Causal Models for Age Categories

The results show that the two subsamples do not behave the same toward the IoT (Table 12). For IoT natives, behavioral intentions are determined by five main factors: performance expectancy ($w_i= 0.547$; $t=5.402$), effort expectancy ($w_i=0,312$; $t=3.893$), social influence ($w_i= -0,128$; $t=-2,282$), perceived risk ($w_i= -0,164$; $t=-2,352$), and facilitating conditions ($w_i= 0,121$; $t=-2,252$). For IoT immigrants, only facilitating conditions ($w_i= 0,445$; $t=3,715$) and performance expectancy ($w_i= 0,271$; $t=2,563$) contribute significantly to their behavioral intentions. The permutation test yields a clearer understanding of the differences between the two groups (Table 13). It indicates that the two groups differ significantly in the contributions of social influence and facilitating conditions to their behavioral intentions. These contributions prevail for IoT immigrants but not for IoT natives. This result means, on the one hand, that IoT immigrants focus essentially on IoT effort expectancy and IoT performance expectancy to define their behavior intentions. On the other hand, for IoT natives, social influence and facilitating conditions play an important role as foregoing factors in their decision making. Moreover, the path coefficient of social influence ($w_i= -0,128$; $t=-2,282$)

has a negative influence on the behavior intention of young consumers. This result means that IoT natives behave in the opposite way to the recommendations of their social environment.

Dependent variable	Independent variable	Standardized path coefficient (coef. with bootstrap)	Standard error (Error of bootstrap)	T (>1.65)	Pr > t (5% risk of error)	Bootstrap interval	
						Lower bound (95%)	Upper bound (95%)
IoT Natives R ² =0.579 Adjusted R ² =0.556	Performance Expectancy	0.547 (0.531)	0.101 (0.086)	5.402	0.000	0.357	0.718
	Effort Expectancy	0.312 (0.288)	0.080 (0.089)	3.893	0.000	0.075	0.502
	Social Influence	-0.128 (-0.231)	0.094 (0.098)	-2.282	0.025	-0.499	-0.105
	Facilitating Conditions	0.121 (0.134)	0.497 (0.506)	2.252	0.027	0.030	0.234
	Perceived Risk	-0.164 (-0.172)	0.070 (0.105)	-2.352	0.021	-0.263	-0.144
	Financial Cost	-0.109 (-0.091)	0.069 (0.114)	-1.563	0.121	-0.319	-0.109
IoT Immigrants R ² =0.656 Adjusted R ² = 0.634	Performance Expectancy	0.445 (0.450)	0.120 (0.168)	3.715	0.000	0.142	0.865
	Effort Expectancy	0.271 (0.276)	0.106 (0.131)	2.563	0.012	0.091	0.546
	Social Influence	0.576 (0.579)	0.343 (0.267)	1.683	0.097	0.097	1.121
	Facilitating Conditions	-0.430 (-0.439)	0.347 (0.260)	-1.241	0.219	-0.992	0.159
	Perceived Risk	-0.097 (-0.095)	0.069 (0.065)	-1.395	0.167	-0.243	0.058
	Financial Cost	-0.139 (-0.148)	0.070 (0.077)	-1.980	0.051	-0.331	-0.003

Table 12. Test of the Moderation Effect of Gender on the Relationships of the Causal Model

Independent variables	Permutation test		
	Difference	P	Significance
Performance Expectancy	0.102	0.604	No
Effort Expectancy	0.041	0.792	No
Social Influence	1.705	0.020	Yes
Facilitating Conditions	1.550	0.030	Yes
Perceived Risk	0.067	0.436	No
Financial Cost	0.031	0.871	No

Table 13. Test of Permutation

6. Discussion and Implications

Industry 4.0 and its new technological paradigm IoT is generating a major change in mindset and consumer lifestyles, especially in the healthcare sector. The main purpose of the current study is to reveal the perceived barriers to IoT adoption in the sphere of eHealth. The study attempts to close the following research gaps revealed during the detailed literature review. a) The adoption of the IoT in eHealthcare is under researched. b) Existing research on eHealthcare adoption is mainly performed from the organizational perspective, that is, eHealth adoption by clinics, hospitals, doctors, and nurses. c) Existing research on eHealthcare adoption mainly ignores the issue of cost. This follows from gap (b), because when doctors and nurses in a hospital are encouraged to adopt IoT, they do not pay for it. Finally, d) most studies on eHealth ignore the age component, and do not explore the differences in IoT adoption in eHealth between young potential users and older ones.

Hypotheses		Results
H1	Performance expectancy positively impacts intention to use healthcare devices by the end-users.	Supported
H2	Effort expectancy negatively impacts intention to use healthcare devices by the end-users.	Supported
H3	Social Influence positively impacts the intention to use healthcare devices by the end-users.	Rejected
H4	Facilitating conditions positively influence the intention to use healthcare devices by the end-users.	Supported
H5	Perceived risk positively influences the intention to use healthcare devices by the end-users.	Rejected
H6	Financial cost negatively influences consumers' behavioral intention to use healthcare devices.	Rejected
H7	Age and gender moderate the effects of performance expectancy, effort expectancy, social influence, and facilitating conditions on consumers' behavioral intention.	Partially Supported

Table 14. Results of the Test of the Research Hypotheses

As illustrated in Table 14, out of six hypotheses, three were rejected (H3, H4, and H5) and three were validated (H1, H2, and H6) for the total sample. The four direct predictors of the UTAUT model were tested on behavioral intention (performance expectancy, effort expectancy, social influence, facilitating conditions, and perceived risk). The findings of this research show a significant positive effect of the constructs performance expectancy and effort expectancy in the UTAUT model for predicting behavioral intention. This result is in line with previous studies (Ciperman et al., 2016; Hoque and Sorwar, 2018), which shed light on the particular importance of performance expectancy and effort expectancy. However, social influence and facilitating conditions are not significant. This finding is not consistent with previous studies (Idrish et al., 2017; Nisha et al., 2019), which highlight that potential users are more sensitive to performance expectancy, effort expectancy, facilitating conditions, and social influence. These conditions are perceived as enablers fostering the adoption of mHealth.

Moreover, these constructs are extended to include perceived risk and financial cost to consider how these two perceived barriers influence the consumers' acceptance in the context of IoT for eHealth.

The findings suggest that the adoption of IoT in eHealth results from a mix of several conditions. It is interesting to note that the current research demonstrates the significance of the financial cost variable for models examining behavioral intentions to use IoT for eHealth. financial cost is found to be one of the main barriers to IoT adoption in eHealth for consumers. This finding has important practical implications for marketing, forming price, and building a strategy for developing new products. It also represents the novel aspect of the current research: to the best of our knowledge, this is the first study to examine eHealth adoption from customers' perspective and to include financial cost as a variable in the

extended UTAUT model. Previous research has used this approach mainly in connection with integrating mobile phones into healthcare (Wallis et al., 2017), that is, such research has proved that mHealth can reduce cost, save time, and increase the interaction between patients and doctors (Hoque, 2016). However, we are not aware of any research in which eHealth in particular is investigated.

Furthermore, this study reveals that the variable of perceived risk has no significant effect on behavioral intention. Neither of these findings are in line with the findings of several previous works, such as Kijisanayotin et al. (2009) and Martins et al. (2014), in which the variables of the initial UTAUT model are confirmed in the healthcare context. This can be explained by the fact that the current research is built from an individual perspective: only real customers who decide to use an eHealth service and pay for it are chosen as the targeted sample.

The moderating effect of gender on IoT behavioral intention does not prove to be significant in influencing effort expectancy, performance expectancy, and financial cost (*Figures B.1 and B.2*). This result is in line with previous studies (Venkatesh et al., 2003, 2012). In the context of the current research, this finding can be explained by the sample composition: only generations X, Y, and Z are considered, and customers from these generations, both men and women, adopt technology more or less equally, that is, the gender differences are less and less significant in these generations.

Another important result of the study is the moderating effect of age. We reveal that consumers demonstrate different behavior depending on their age group, according to the GT (Bawack and Kamdjoug, 2018; Noble et al., 2009). Moreover, this study proves that the behavior differs significantly in two age groups: people younger than 20 years (the first entirely digital generation) and people older than 20 years old (*Figures C.1 and C.2*). This allows us to propose two new categories to name these distinct clusters: *IoT natives and IoT immigrants*. The emergence of these two groups is very meaningful, in our view, because the concept of IoT itself is approximately 2 decades old, which is the same age as the so-called Gen X. Our findings show that among IoT immigrants (i.e., people older than 20), for Gen X, the probability of adopting IoT decreases, while among IoT natives, it increases. Therefore, age is positively negatively connected to IoT acceptance. This is in line with previous findings that age influences adoption of online shopping and e-commerce in general, as the younger tech-savvy generation is driving technological change by actively mastering digital information (Lichy, 2016) while older generations are connected but lack digital communication skills (Hartman and McCambridge, 2011).

6.1. Theoretical Implications

The major hypotheses proposed in our research model are consistent with the UTAUT results. This provides further confirmation of the generalizability of the UTAUT model. Moreover, the contextual insights generated by the current study add to the existing state of the art in the area of technology adoption. We now consider the implications of the results for financial cost and perceived risk toward the IoT for eHealth. The findings show that these two predictors do not influence consumers' willingness to adopt connected devices for eHealth in the same way.

The theoretical contributions concern three main issues: (1) the extension of the traditional UTAUT model of technology acceptance (Venkatesh et al., 2003, 2012); (2) the importance of the contextual use of IoT for eHealth (Goad et al., 2020); and (3) the identification of two adopters profiles: IoT natives and IoT immigrants.

First, our contributions further extend previous studies that apply and extend the UTAUT, which tend to focus more on perceived benefits. Previous works authors have predicted a

positive relationships between perceived benefits and performance expectancy and between perceived trust, and performance expectancy, for example, in the context of ubiquitous healthcare services (Jang et al., 2016). Thus, we consider that even if end users trust and perceive the benefits of the healthcare services, they might not adopt them owing to their perceived high costs. Thus, financial cost and perceived risk are crucial factors to gain a better understanding of user acceptance of a technology in the context of IoT for eHealth. In addition, referring to Williams et al. (2015), the most frequently used external variables affecting performance expectancy, effort expectancy, social influence, financial cost, and behavioral intention, reveal that self-efficacy (21 occurrences) is the most highly applied external variable, closely followed by attitude (20) and confidence (18). The external variable perceived risk is used only 10 times and the financial cost factor is not tested.

Our second main contribution concerns the contextual use of these connected devices. In previous studies, a large range of authors have investigated the acceptance of connected healthcare devices by elderly consumers (Cimperman et al., 2016; Sivathanu, 2018). The novelty of this study is that it considers various age groups and compares their intentions to use IoT for eHealth.

Third, to the best of our knowledge, no previous research compares IoT potential users by referring to a generation classification. Here our main contribution is the identification of two typologies of adopters: IoT natives and IoT immigrants.

Considering age as a moderator, the two extended variables financial cost and perceived risk seem to have a heavy and different role in an individual's willingness to adopt connected devices to monitor their health condition. In fact, for *IoT natives*, financial cost is significant and acts as a barrier toward IoT healthcare adoption. This finding is in line with Venkatesh et al. (2012), who report that, in the context of individual consumption, the consumer must accept the monetary cost associated with the use of the product. Accordingly, the acquisition and recurring costs that are associated with the use of IoT for eHealth can have a significant impact on an individual's adoption decision. This impact may be more significant when the individual has financial constraints (Hart and London, 2011). However, perceived risk has no impact on young adopters. On the contrary, IoT immigrants are more likely to consider the perceived risk of the connected devices while monitoring their health. This variable is regarded as a barrier to IoT adoption. Potential users could be reluctant to use eHealth technologies owing to these negative perceptions.

6.2. Practical/Managerial Implications

The empirical outcomes of our investigations have implications for corporate managers as well as policymakers. The empirical findings highlight that the adoption of IoT for eHealth is not limited to patients (Wang and Hsieh, 2018; Martínez-Caro et al., 2018), as a digitalized world connects all roleplayers via connected devices that allow consumers to monitor their health condition.

In accordance with the empirical results, several practical implications are proposed to aid marketing managers, strategists, and policymakers to better understand the factors that discourage or support IoT adoption in the context of eHealthcare. This study addresses this gap by proposing relevant hypotheses and performing empirical analysis.

Connected devices applied in a medical context should be divided into groups according to the consumers' profile: whether they are IoT natives or IoT immigrants. Considering these two profiles of IoT adopters in the healthcare context, managers and practitioners should

adjust their medical devices. For IoT natives, the industry should offer connected devices at low prices to be more attractive. They should also guarantee the performance of connected devices and reduce the effort required to use them. Unlike IoT natives, for IoT immigrants, social influence and facilitating conditions play a heavy role in IoT eHealth adoption. As these consumers have little experience of connected devices, their acceptance is influenced by their friends, family members, etc. and they need additional information from professionals and/or providers on how to use these devices. In addition, regarding the extended variables, IoT immigrants are more likely to pay attention to perceived risk related to IoT for eHealth. For these end users, these devices might not respect their privacy and personal information. However, their decision to adopt the devices is not conditioned by financial cost. IoT immigrants are willing to pay more to use connected objects if they consider them to be secure and do not perceive the tools as unsafe. This enables them to be more engaged in their healthcare treatment, as they can trust the healthcare system via the IoT.

In addition, the adoption of IoT for eHealth by Gen X, Y, and Z is potentially set to induce significant social change. As a majority of people start to use connected devices to monitor their health condition, governments can increase healthcare efficiency by providing IoT-based services to citizens. For example, as the use of IoT solutions and connected devices enables monitoring patients in real time, it will be possible to avoid unnecessary visits to doctors and to reduce hospital saturation (Perwej et al., 2019).

In the context of the 4th Industrial Revolution and rapidly developing IoT technologies within the healthcare sector, it is particularly important to investigate consumers' adoption of new products and services (Caputo et al., 2018). By doing this, the current research highlights the key factors enabling intention to use IoT for eHealth and sheds light on the main perceived barriers against adoption of these devices. This study also seeks to extend existing knowledge about the IoT and to help IoT providers and designers by identifying specific predictors that determine the willingness of IoT digital natives and IoT digital immigrants to buy and use IoT-based devices.

6.3. Limitations and Future Research Avenues

This study is not without limitations, as it involves potential users based in only one country. The results of the current study cannot be generalized to a worldwide segment of IoT for eHealth, as we focus on French IoT natives and IoT immigrants. Thus, future research should conduct cross-country benchmarking of similar research. In addition, even though the sample size is in line with other studies related to IoT and the use of PLS-SEM avoids the statistical limits related to the sample size, it would be useful to replicate the study with a larger sample and to integrate additional control variables. This would enable us to better figure out the specificities (features) of IoT natives and IoT immigrants. For example, it would be useful to consider additional properties of respondents' innovativeness, personality traits, and privacy concerns. Other characteristics, like health locus of control (Ross et al., 2015) and consumers' resilience (Grol and De Raedt, 2015) could enhance understanding of the behavioral intentions of IoT potential users.

7. Conclusion

This study focuses on one of the most important drivers of the 4th Industrial Revolution, namely, the IoT, and particularly, the adoption of IoT in healthcare. The key research aim is to reveal the barriers to eHealth adoption. The literature review reveals clear research gaps, including the scarcity of eHealthcare research in general, the lack of a customer perspective, and finally, the neglect of the influence of financial cost and age on acceptance of IoT-based healthcare devices. This study attempts to close these gaps by suggesting an extended

UTAUT model including financial cost and perceived risk and testing its validity in the context of IoT adoption for eHealth.

This study makes several theoretical contributions by proposing relevant hypotheses and empirically investigating them. Based on 268 potential users of IoT-based healthcare devices in France, we find that performance expectancy and effort expectancy are the key predictors positively influencing behavioral intention to use IoT for eHealth. The first important result of the research is that financial cost is the basis for customers' buying decisions and therefore, a high price of IoT in healthcare is the biggest barrier to its acceptance. Using structural modeling, this study shows that the financial cost of using IoT in eHealth is the main barrier to IoT adoption: even if end users trust the technology and the perceived benefits of the IoT-connected devices are high, consumers might not adopt them because of high perceived costs. The second important result is the proven moderating effect of age. Age is found to be an influential moderator of customers' intention to use IoT in eHealth, inspiring the specification of two new user categories: IoT natives, that is, people younger than 20 years (the first entirely digital generation) and IoT immigrants, that is, people older than 20 years. The third result is also important: the moderating effect of gender is insignificant among Gen X, Y, and Z, (i.e., in the process of eHealth adoption, the gender differences are smoothed). These results have important theoretical and practical implications in the context of the 4th Industrial Revolution for IoT developers, marketers, and policymakers who need to consider the revealed user categories, perceived barriers, and incentives for IoT adoption to better understand the factors that hamper or enable the adoption of connected devices in the context of healthcare. At this point, the adoption of the IoT in eHealth has proved to be one of the most important features of Industry 4.0 and it has a very promising future.

Declaration of interest:

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Appendix A

Variables	Measurement items	References
Performance Expectancy	[PE1] Using IoT products for healthcare would improve my performance	Foon and Fah (2011), Luarn and Lin (2005), Venkatesh and Zhang (2010)
	[PE2] Using IoT products for healthcare would save me time	
	[PE3] I would use IoT products for healthcare in any place	
	[PE4] I would find IoT products for healthcare useful	
Effort expectancy	[EE1] Learning to use IoT products for healthcare is easy for me	Foon and Fah (2011), Luarn and Lin (2005), Sripalawat et al. (2011), Venkatesh and Zhang (2010)
	[EE2] Becoming skillful at using mobile banking is easy for me	
	[EE3] Interaction with IoT products for healthcare is easy for me	
	[EE4] I would find IoT products for healthcare easy to use	
Social Influence	[SI1] People who are important to me think that I should use IoT products for my healthcare	Foon and Fah (2011), Venkatesh and Zhang (2010), Venkatesh et al. (2003)
	[SI2] People who are familiar with me think that I should use IoT products for my healthcare	
	[SI3] People who influence my behavior think that I should use IoT products for my healthcare	
	[SI4] Most people surrounding me use IoT products for their healthcare	
Perceived Risk	Using IoT products for my healthcare is risky	Stone and Gronhaug (1993)
	I feel that using IoT products for my healthcare would cause me a lot of trouble if something went wrong.	
	Basically, I'm sure I would make a mistake if I were to use IoT products for my healthcare*	
Facilitating conditions	[FC1] My living environment supports me to use IoT products for my healthcare	Sripalawat et al. (2011), Venkatesh and Zhang (2010), Venkatesh et al. (2003),
	[FC2] My working environment supports me to use IoT products for my healthcare*	
	[FC3] Using IoT products for my healthcare is compatible with my life	
	[FC4] Help is available when I encounter problems using IoT products for my healthcare	
Financial Cost	[FIC1] The cost of using IoT products for healthcare is higher than using other healthcare products	Luarn and Lin (2005), Sripalawat et al. (2011)
	[FIC2] The IoT products for healthcare cost me lot of money	
	[FIC3] Using IoT products for healthcare is a cost burden to me	
Behavioral Intention	[BI] I intend to use IoT products for my healthcare	Venkatesh and Zhang (2010)

Table A.1 Measure Scales' Items and References

	Performance Expectancy	Effort expectancy	Social Influence	Facilitating conditions	Perceived Risk	Financial Cost	Behavioral Intention
PE1	0.870	0.507	0.503	0.516	-0.127	0.093	0.455
PE2	0.884	0.608	0.505	0.503	0.081	0.086	0.474
PE3	0.896	0.584	0.520	0.522	-0.037	0.033	0.403
PE4	0.839	0.398	0.614	0.519	-0.031	-0.066	0.516
EE1	0.564	0.918	0.243	0.235	0.148	0.099	0.403
EE2	0.571	0.940	0.248	0.237	0.123	0.162	0.572
EE3	0.562	0.934	0.229	0.215	0.075	0.141	0.603
EE4	0.565	0.932	0.266	0.255	0.122	0.208	0.584
SI1	0.559	0.182	0.881	0.415	-0.007	-0.011	0.391
SI2	0.535	0.182	0.896	0.424	0.061	0.063	0.392
SI3	0.446	0.243	0.812	0.499	0.008	0.112	0.310
SI4	0.539	0.309	0.846	0.425	-0.025	0.111	0.394
FC1	0.559	0.182	0.631	0.915	-0.007	-0.011	0.391
FC2	0.535	0.182	0.596	0.924	0.061	-0.063	0.392
FC3	0.539	0.309	0.546	0.825	-0.025	-0.111	0.394
PR1	-0.029	0.110	0.009	0.018	0.950	0.114	0.115
PR2	-0.030	0.127	0.011	-0.001	0.914	0.167	0.089
FIC1	-0.003	0.097	0.072	0.051	0.110	0.784	0.124
FIC2	-0.055	0.081	-0.043	-0.046	0.191	0.721	0.071
FIC3	0.095	0.177	0.095	0.083	0.109	0.909	0.226
BI	0.507	0.635	0.435	0.442	0.111	0.202	1.000

Table A.2 Cross-Loadings of the Items with the Measure Scales

Appendix B

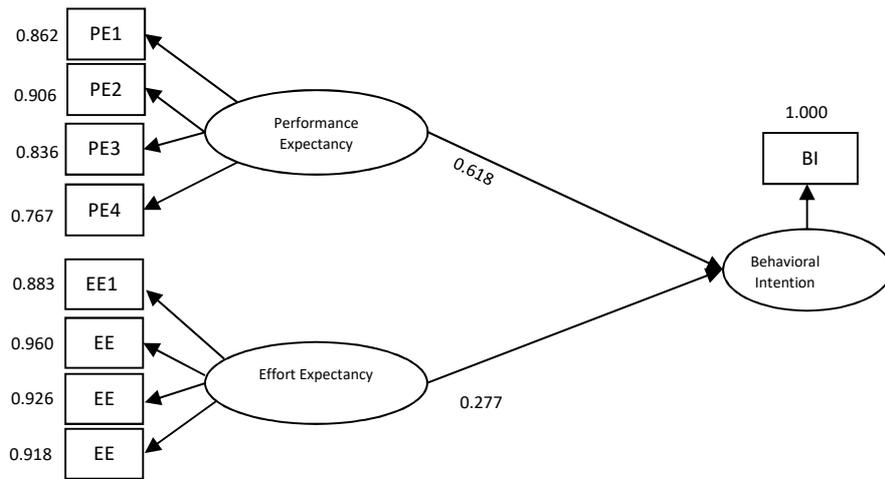


Figure B.1 Validated relationships for the male group

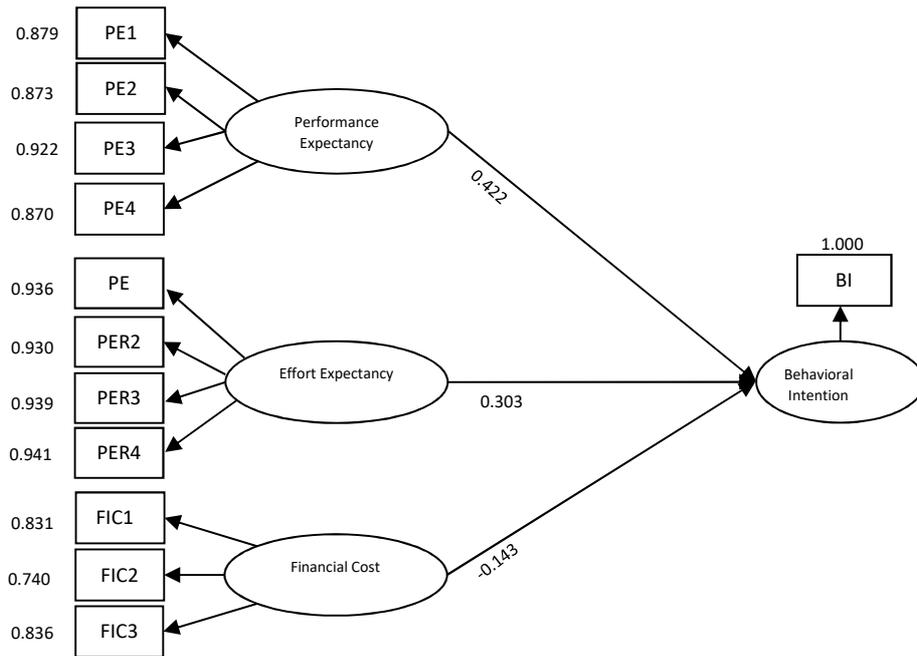


Figure B.2 Validated relationships for the female group

Appendix C

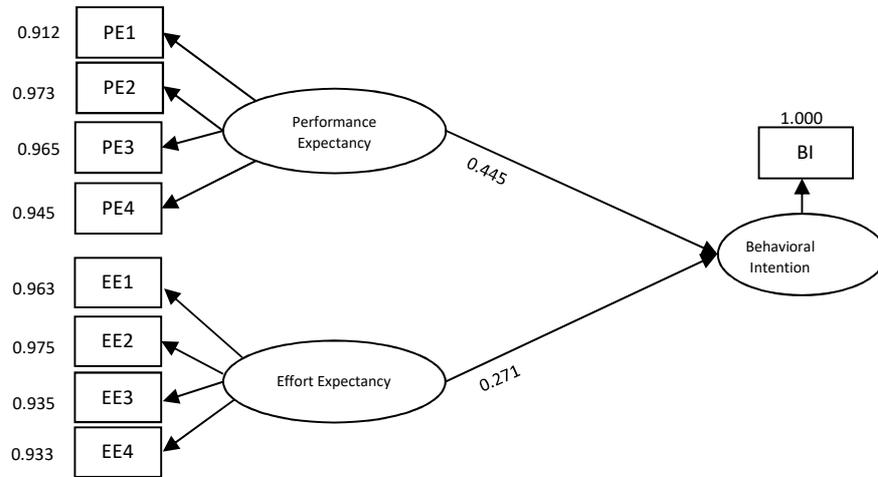


Figure C.1 Validated relationships for the under-20-year group

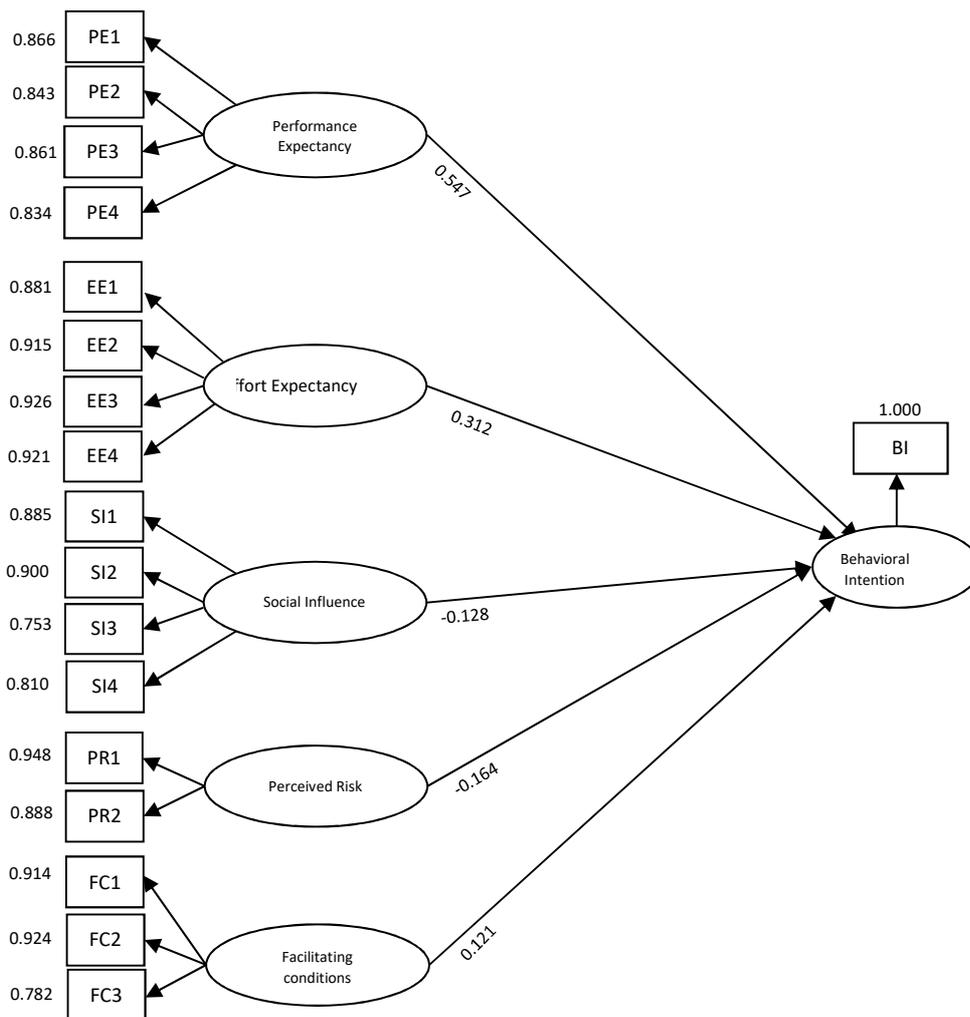


Figure C.2 Validated relationships for the over-20-year group