The Impact of IoT Smart Home Services on Psychological Well-Being

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The Impact of IoT Smart Home Services on Psychological Well-being

Abstract

Smart home services are a new generation of consumer services. Supported by the Internet of Things (IoT) technology, they deliver security, comfort, entertainment, assisted living, and efficient management of the home to improve the quality of life of consumers. As the availability of smart home services expands, there is still a lack of understanding of what motivates their continuing use and how the penetration of smart devices and services in the home environment affects individual well-being. We develop a research model combining hedonic and eudaimonic motivations with the unified theory of acceptance and use of technology 2 (UTAUT 2) to evaluate the impacts on well-being. The model is estimated using partial least squares based on a sample of 260 survey responses. The results show that hedonic motivation associated with the adoption of some smart home services moderates continuing use. Additionally, the results suggest a positive relationship between the use of IoT smart home services and well-being. Furthermore, hedonic and eudaimonic motives have a substantial effect on the use behavior of smart home services and ultimately on well-being.

Keywords: IoT, smart home services, well-being, hedonic motivation, eudaimonic motivation.

The impact of IoT smart home services on well-being

1. Introduction

Advances in electronic hardware miniaturization and mass production have paved way for the proliferation of information and communication technologies (ICT). Particularly over the last decade, the Internet of Things (IoT) technology has rapidly evolved resulting in an abundance of related products and services. IoT technology encompasses all ‘smart’ devices that have basic computational capabilities and communication functionalities along with features that enable interactivity with the environment, people, and other devices (Hsu & Lin, 2016). A subset of IoT technology targets the household environment, giving rise to the term ‘smart home’ - in reference to homes where several domestic appliances are connected through the use of IoT technologies (Kim, Park, & Choi, 2017).

Several commercial interests have pushed the development of the smart home market. For instance, the European market for smart homes amounts to 15.171 M€ with a household penetration of 12.2% in 2019 and anticipated to reach 31.717M€ with a penetration rate of 24.6% in 2023 (Statista, 2018). Today, mobile carriers and cable TV businesses, facing stagnation from traditional market models, seek new business models to expand revenue streams, and IoT smart home products and services presents a substantive appeal with great potentials (Park, Kim, Kim, & Kwon, 2018). Technology giants such as Google, Microsoft, Apple, Amazon, AT&T, and others have developed strategies to monetize on the smart home market. They also recognize that smart home services present the opportunity to gather rich data on the consumer base (ABI, 2018). Governmental agencies also have vested interest in smart homes. Many countries have implemented strategies to balance impacts of climate change and fluctuations of energy prices by investing in the development of smart grid and smart cities. Related infrastructure taps into the smart home market to provide better services to citizens, including energy monitoring and waste management (Balta-Ozkan, Boteler, & Amerighi, 2014). In Europe, the European Commission included smart homes as one of the ten priority action areas in their Strategic Energy Technology Plan (European-Commission, 2015).

Technologies for the household are typically advertised by vendors and service providers as a means to improve quality of life, simplify or automate tasks, and save time and energy. Changes in family structures and society, shrinking of traditional families, higher divorce rates, and longer life expectancy have led to more individualized household environments, and thereby, an increasing dependence on technology as a means to support intrinsic needs of humans to connect with others (Davidoff, Lee, Yiu, Zimmerman, &

Dey). For example, smart home technologies have a positive impact on the physical well-being of the elderly by assisting them overcome certain limitations that stem from aging (Henkemans et al., 2010).

However, technology adopted and continually used for extended duration impacts not only the quality of life but also the state of well-being of individuals. Such an example is the mass penetration of Internet technology in households of developed countries. Although families and individuals use Internet for different purposes such as entertainment, communication, dating, on-line education, and business, it also has brought negative consequences for human well-being, like the appearance of new psychological disorders such as internet addiction disorder, online gaming addiction, and depression (Cotten, Ford, Ford, & Hale, 2012; Ha et al., 2007). A few studies have investigated the impact of IoT on the well-being of individuals. None of the studies have explored the impact of IoT technologies on the psychological well-being of a person.

The purpose of this study is to gain insights into how smart home technologies and services are adopted and used by individuals in their daily lives, and to what extent it is perceived to impact individual well-being. It is to gauge whether well-being is enhanced by contemporary technologies such as IoT in comparison to how it has been understood historically. To this end, we conduct an exploratory study on the relationship between IoT smart home services and well-being, by applying theoretical models from information systems (IS) and and published research from psychology. The contributions of this study are two fold. First, it aims to expand technology adoption theories in IS to include eudaimonic motivation and present a new model to explain well-being from the perspective of IoT-based services. And second, the study aims to assess the relationship between IoT smart home services and the well-being of consumers.

The next section provides an overview of the meaning and relevance of IoT smart home services as well as conceptions of well-being based on prior research. Research hypotheses and the proposed model are presented in section 3. Section 4 describes the methods for measurement and collection of data, and section 5 presents the analysis and results. Finally, the implications and limitations of the study are discussed in section 6.

2. Theoretical Background

2.1. The smart home service

Prior studies propose different conceptualizations of smart home services (Darby, 2018; Park et al., 2018). Generally speaking, they are services associated with home automation based on products such as IoT smart devices that can be bought off-the-shelf or installed at home. Smart home services provide functionalities such as automated device actuation, remote access monitoring and control, media access, and energy savings for home residents. In many instances, the services are linked to a service provider who may also provide the installation and setup of proprietary devices at home. In the context of this study, IoT smart home service is defined as the IoT based functionality provided to the household, by a service provider or third party, to allow ubiquitous and interactive control of the home by its owners. Balta-Ozkan et al. (2014) identifies three categories of smart home services: lifestyle support, energy consumption management, and safety.

2.2. Determinants of the smart home services

As discussed earlier, the potential market for IoT smart home services is still in its early stages. As such, existing research has primarily focused on the determinants of its adoption. Based on an investigation of experts from 19 companies, Kuebel and Zarnekow (2015) identified 34 factors that impact the adoption of IoT smart home services. They found that perceived ease of use (related to the complexity of using the system), and perceived usefulness (encompassing reliability, expected benefits, and financial costs) are the primary constructs that impact the adoption of smart home platforms. Their study focused on services associated with energy consumption management such as energy efficiency, convenience, and comfort and security, and thus represented a strictly utilitarian perspective of smart home services.

In a study to establish the relationship between smart home services and value representation for the customer, Park et al. (2018) defined energy conservation services to be of economic value, entertainment services to represent hedonic value, healthcare and security services to denote security value, and home convergence, appliances, and automation to embody comfort value. Their study found that security value holds the most effect in the intention to adopt smart home services, and perceived by the study participants as more closely related to well-being. This was followed by economic value and comfort value, with hedonic value having the least effect in the intention to adopt smart home services.

Research has also shown well-being benefits of smart homes, assigning greater importance to services within the lifestyle support category, such as communications, entertainment, e-health, assisted living, and convenience and comfort (Balta-Ozkan et al., 2014). This was confirmed by Y. Kim, Park, and Choi (2017), who proposed a value-based adoption model by extending the study by H. W. Kim, Chan, and Gupta (2007), to reflect the less technical profile of consumers of smart home services compared to the more technical profile of the early adopters of technology. The model combined variables from the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003) and elaboration likelihood model (Bhattacherjee & Sanford, 2006), and the results showed that perceived value would highly influence the decision to adopt smart home services. The study also found that perceived value is influenced by perceived benefits (i.e., entertainment, usefulness, and facilitating conditions) and to a lesser extent by perceived sacrifice (i.e., privacy risk, innovation resistance, technicality, and perceived fee).

The review of literature indicates that most studies only investigated factors impacting the adoption of smart home technology or services, and were conducted as some adaptation or extension of the Technology Acceptance Model (TAM) (see Table 1). However, TAM is widely criticized (Chuttur, 2009; Lim, 2018) since it only employs two key constructs (perceived usefulness and perceived ease of use) to explain factors influencing user's adoption of technology. Several revisions and theories have been proposed to address the limitations of TAM. In particular, UTAUT and its later revision UTAUT2 (Venkatesh, Thong, & Xu, 2012) have become influential alternatives due to the comprehensive nature of the model and substantial empirical support (Tam, Santos, & Oliveira, 2020). UTAUT was developed from an employee perspective in a workplace setting, and considered user perceptions of performance expectancy, effort expectancy, social influence, and facilitating conditions. On the other hand, UTAUT2 targeted a broader technology consumer perspective (Tamilmani, Rana, & Dwivedi, 2020), and included contextual factors such as price, habit, and hedonic motivation. Thus, UTAUT2 is used in this study as the theoretical foundation due to its applicability to IoT and its relationship to the consumer context that we seek to investigate.

Table 1. **Studies on smart home adoption**

Authors	Year	Title	Framework	Drivers	Data	Comments
Kim, Park & Choi	2017	A study on the adoption of IoT smart home service: using the Value-based Adoption Model	VAM; TAM	• Perceived sacrifice: privacy risk, innovation resistance, technicality, perceived fee • Perceived benefit: facilitating condition, perceived usefulness, enjoyment • Perceived value • Variety seeking • Attitude • Intention to use	269 survey responses	Contrasts the less technical profile of the potential consumers of smart home services as opposed to the more technical profile of the early adopters of technology.
Kuebel & Zarnekow	2015	Exploring Platform Adoption in the Smart Home Case	TAM	• Characteristics of the supporter: reputation, support infrastructure. • Characteristics of the platform: compatibility, complexity, flexibility, complement range, privacy, financial costs, reliability • Platform support strategy: appropriability, distribution • Other stakeholders: suppliers, development, supporters	interviews with 19 companies and 21 middle and top senior executives in SH business	Shows that the perceived ease of use, (relating to the complexity factor of using the system), and the perceived usefulness, (encompassing the factors reliability, expected benefits, and financial costs), are the main constructs that impact the adoption of smart home platforms.
Balta-Ozkan, Davidson, Bicket, & Whitmarsh	2013	Social barriers to the adoption of smart homes Social barriers to the adoption of smart homes	N/A	• Fit to current and changing lifestyles • Interoperability • Administration • Reliability • Privacy and security • Trust • Costs	Eight industry expert interviews and two deliberative workshops with 30 participants each, in 2 different UK cities.	Shows the barriers for adoption of the smart home that can be related to eudaimonia. Some of the identified barriers, such as the changes to lifestyle, the loss of privacy, and lack of trust, may reflect inversely on eudaimonia.
Saad Al-Sumaiti, Ahmed, & Salama	2014	Smart Home Activities: A Literature Review	SHEMS	• SHEMS activities: optimization, control and automation, communication systems	literature	The study runs a literature review of smart-home systems, particularly focused on automation and energy management systems.
Yang, Lee, & Zo	2017	User acceptance of smart home services: An extension of the theory of planned behavior	TPB	• Automation • Mobility • Inter-operability • Security/privacy risk • Physical risk • Trust in the service provider	231 online survey responses	Using TPB evidence that mobility is one major driver for adoption; thus, providers should provide such functionality to allow consumers to access and control their homes while on the move, accessing from mobile devices.
Balta-Ozkan, Boteler, & Amerighi	2014	European smart home market development: Public views on technical and economic aspects across the United Kingdom, Germany, and Italy	N/A	• Energy and cost savings • Tangible benefits improving the quality of life • Environment • Transparency	Six public deliberative workshops held in three distinct European countries with groups of 24-30 persons per workshop	The study was conducted in the EU, on the United Kingdom, Germany, and Italy, evidencing an intrinsic concern of Europeans towards balancing costs and energy consumption with a greater quality of life and environmental protection, thus approaching definitions of eudaimonia.
Park, Kim, Kim, & Kwon	2018	Smart home services as the next mainstream of the ICT industry: determinants of the adoption of smart home services	TAM	• Perceived cost • Compatibility • Perceived security • Perceived system reliability • Perceived control • Perceived connectedness • Enjoyment	799 online survey responses	The drivers used in the model are related to consumer values. The categories of values are close to the service domain categories established in Balta et al. 2014
S. Darby	2018	Smart technology in the home: time for more clarity	N/A	• Energy efficiency • Automation • Remote connectivity • Environment impact • Pleasant living environment	literature	The study expresses an alternative point of view of the definition of smart-homes and the side-effects the technology involved has on the quality of life of their users, as well as arguing that the promised benefits associated with smart homes are indeed as large as advertised.

2.3. Conceptualization of well-being

Well-being is a highly debated subject in philosophy, and involves differing perspectives and conceptualizations linking eudaimonia and hedonia. A systematic review of literature traces the roots of hedonia and eudaimonia to ancient Greece (L. Henderson & Knight, 2012) and offers a variety of different definitions (Huta, 2018). Epicurus and other philosophers equated the hedonic perspective of well-being with "...the positive emotional states that accompany satisfaction of desire; therefore, experiences of pleasure, carefreeness, and enjoyment were considered reflective of well-being" (Diener, 2009). The eudaimonia perspective was introduced by Greek philosopher Aristotle who conceptualized it as "living a life of excellence and virtue" (Henderson & Knight, 2012). Although sound reasoning exists to consider eudaimonia distinct from hedonia (Huta, 2018), modern researchers agree that the conceptualization of well-being should integrate both views. M. E. P. Seligman, Parks, and Steen (2004) introduced the concept of hedonia as the route to greater happiness, and later M. E. Seligman (2012) extended this viewpoint to include the concepts of achievement and relationships, and describing it as 'flourishing'. Keyes (2007) expanded on promoting and protecting metal health to include the facets of hedonic well-being and eudaimonic well-being in psychological and social functioning in life. He concluded that although hedonia and eudaimonia are highly correlated, they are, in fact, distinct pathways of behavior that can be pursued separately and still have associated well-being benefits. Keyes (2007) suggested that both perspectives should be integrated in order to allow for a more comprehensive understanding of well-being, as they appear to be strong predictors of "flourishing" when considered together. Although eudaimonic pursuits seem to deliver higher well-being benefits, a life abundant in both hedonic and eudaimonic pursuits is associated with the greatest degree of well-being benefits (Huta & Ryan, 2010).

Huta and Waterman (2014) conducted a review of hedonia and eudaimonia reinforcing the previous conclusions. Their study raised concerns regarding the empirical methods used to evaluate well-being as (p.1426) "...findings based on different operationalizations can be quite discrepant; definitions of eudaimonia and hedonia sometimes fall into different categories of analysis (e.g., when eudaimonia is described as a way of functioning, hedonia as an experience); and the terms eudaimonia and hedonia are sometimes defined vaguely or applied to concepts that may be mere correlates.". To counter these challenges, the authors suggested: (1) use of common terminology and classification to discuss conceptual and operational definitions (degree of centrality, close-to-the-core, and major correlates); (2) identification of the category that the definitions represent (orientations, behaviors, experiences, and functioning); and (3) identification of the level of measurement, if a definition is used either for trait or state comparisons. In exploring the impact of hedonic and eudaimonic behavior on well-being, similar challenges were identified by L. W. Henderson, Knight, and Richardson (2013). The authors applied time-use research methods to define the nature of the relationship between time and intensity of hedonic and eudaimonic activities, and how this relates to well-being. An initial assessment of the well-being self-evaluation of the participants in their study was done using multiple distinct scales. The activities of the participants were then followed up over a period of time, while the participants kept a diary of their state on the activity. The measurement of the well-being of the participants was based on the hedonic and eudaimonic motives for activities (HEMA) scale proposed by Huta and Ryan (2010). The findings of the study indicated the subjective nature of hedonic and eudaimonic perceptions based on the individual's intrinsic motivations, and showed that the same activity can be perceived as hedonic or eudaimonic, depending on the person's self-evaluation. This was also confirmed by another investigation by Oliver and Raney (2011).

The conceptualizations and measurements of both hedonic and eudaimonic well-being are the subject of debates (Kristjánsson, 2018), especially the latter. Eudaimonic accounts of well-being have been historically connected with theories of virtue ethics, which consider the actualization of moral and intellectual virtues an ineluctable part of a flourishing life. Dating back to Aristotle, those accounts are typically grounded in realism about selfhood. An argument is that the "mirror" of self-conceptions is an unreliable guide to who we are deep down (because of human beings' lack of self-transparency), and hence, peer-reports rather than self-reports are needed to gauge eudaimonic motivations. However, as peer-reports of difficult-to-assess virtues are hard to gather, most contemporary scales rely on self-reports of eudaimonic well-being (Kristjánsson, 2018).

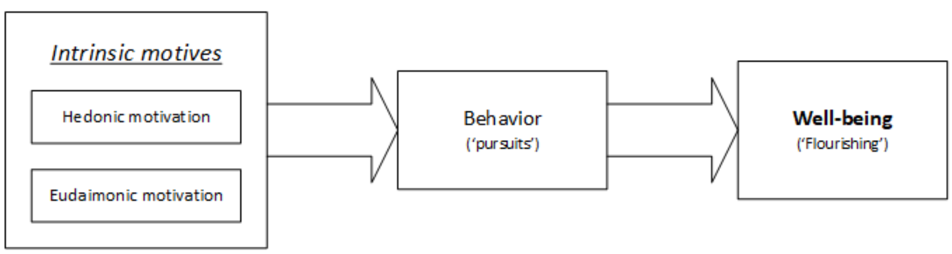


Figure 1. Conceptual model of psychological well-being

Based on the literature and analysis discussed above, a conceptual model relating the intrinsic motives of hedonic and eudaimonic motivations and their impact on behavior and well-being is shown in Figure 1. In this conceptual model, intrinsic motives are a person's drive to pursue or engage in a behavior (or pursuit). An individual pursuing entertainment, fun, pleasure, or similar that may lead to a positive emotional experience represents hedonic motivation. On the other side, an individual pursuing personal growth or development, social connection, or similar, that may lead to a positive cognitive and emotional experience (Marikyan, Papagiannidis, & Alamanos, 2020) would be more closely identified as eudaimonic motivation.

The behavior is the set of activities performed to in conduct of these pursuits. Well-being is the outcome or reward of the behavior, and assumed to be positive (i.e., flourishing).

3. Research Model and Hypotheses

The primary hypothesis of this study is that technology-based IoT smart home services have an impact on individual well-being. As discussed previously, UTAUT2 is robust in explaining the adoption and continuing use of technology, but the model has not been applied to the context of IoT smart home services. Moreover, adoption studies tend to investigate technology from a point of how it supports user activities, as opposed to its functional purposes of accomplishing a pursuit towards well-being with reduced effort. Additionally, although IS theories have identified drivers that influence user behavior towards adoption and continuing use of technology, hedonic and eudaimonic motives, as shown in Figure 1, are also drivers that influence well-being through behavior engagement. Therefore, to test our hypothesis, we propose a research model by replacing the broad scope of behavior or 'pursuits' in Figure 1 with a more conditioned set of behavior that results from the continuing use of IoT smart home services. The research model uses UTAUT2 to define the constructs that impact the behavioral intention to use technology-based IoT smart home services, along with hedonic and eudaimonic motivations as drivers that reflect well-being outcomes. The model is presented in Figure 2.

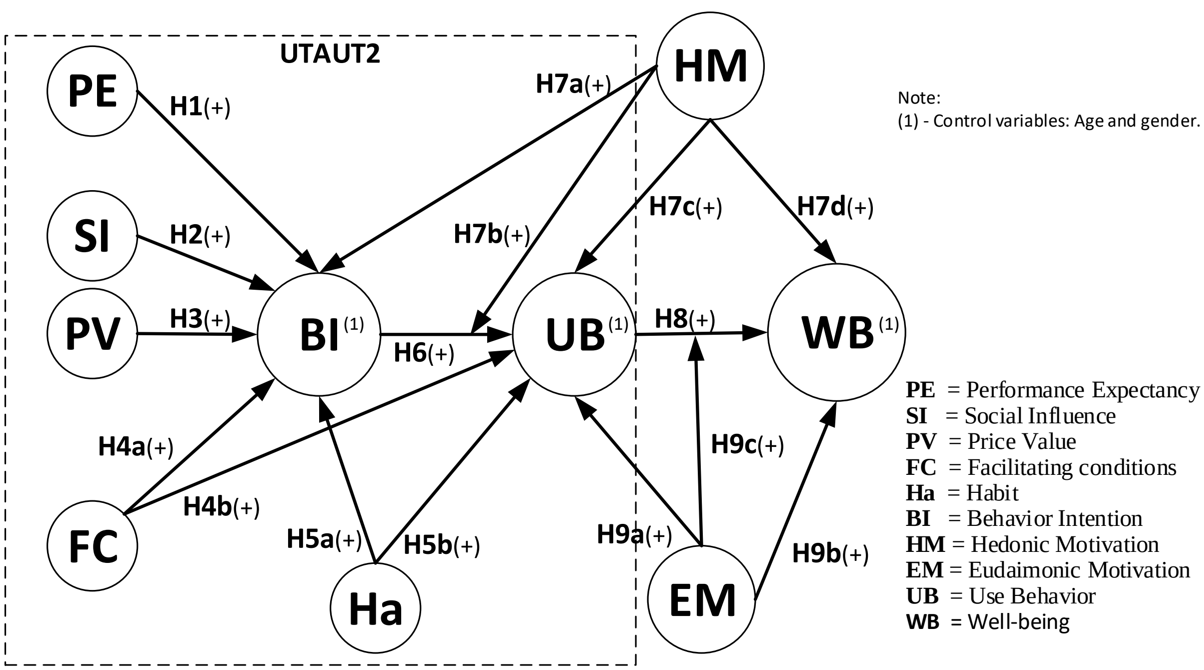


Figure 2. Research model

The constructs in the dotted box are independent variables based on UTAUT2. The dependent variable, well-being (WB) is assessed by combining the UTAUT2 constructs with hedonic motivation (HM) and eudiamonicm motivation (EM).

Performance expectancy

Performance expectancy is based on the perceived usefulness of technology (Davis, 1989) and refers to an individual's perception that technology facilitates the completion of a task (Venkatesh et al., 2003). The construct represents a utilitarian value, and has been shown to have a strong influence on the acceptance and use of information systems. Therefore, it is likely that performance expectancy also strongly influences the adoption and use of IoT smart home services. When using a smart home service, the user may expect to benefit from improving the conditions and functions within the household while spending less energy or time. Performance expectancy is thus a predictor of behavior intention. Therefore,

H1: Performance expectancy of IoT smart home services has a positive impact on behavioral intention.

Social influence

Social influence relates to the extent to which individuals perceive that important people (e.g., family and friends) believe they should use an IS (Venkatesh et al., 2003). In the context of the home environment where the smart home service is used, the family structure or household composition will influence the need to adopt the service and the degree of consumption of the features provided. In addition, changes in modern family structures (e.g., nuclear families using IoT services to stay in touch with extended family members, singles parents using IoT products to monitor children, watching activities of indoor pets) may also lead to increasing use of IoT services across households. Thus,

H2: Social influence associated with IoT smart home services has a positive impact on behavioral intention.

Price value

Price value is the relationship established by the consumer between the monetary cost of a product or service and its valued benefits (Venkatesh et al., 2012). With IoT smart home services, the pricing scheme may be defined either by the type of service/feature or by the time/use of consumption. The consumer of the service may have different perceptions of value based on the feature or use of the service (for example, paying a monthly or annual subscription fee for surveillance services to improve security, paying an hourly rate for better efficiency of climate control services, or pay-per-use of entertainment services). Therefore,

H3: Price value associated with IoT smart home services has a positive impact on behavioral intention

Facilitating conditions

Facilitating conditions represent the degree of a consumer's belief in the organizational infrastructure and technical support available with smart home services (Venkatesh et al., 2012). The construct implies that, having easy access to full technical support and assistance at any time, or having access to training resources influences the adoption and use of a smart home service. For instance, a user of the service with better access to training materials and resources on how to remotely operate home appliances, schedule actions, or automate tasks will be more likely to adopt and continue to use the service when compared to a consumer lacking such resources. Thus,

H4a: Facilitating conditions associated with IoT smart home services have a positive impact on behavioral intention.

H4b: Facilitating conditions associated with IoT smart home services have a positive impact on use behavior.

Habit

Habit is the extent to which individuals tend to perform behaviors through learning, followed by some degree of repetition (Venkatesh et al., 2012). Consumers of IoT smart home services may develop distinct habits depending on the features of the service that are more meaningful or useful to them. For example, a person suffering from blindness may develop the habit of using the voice assist features of the IoT smart home service to receive information on the home environment, monitor events, or trigger voice commands to execute tasks. Habit may also develop through the repeated use and reliance on automation features in the IoT smart home service. For example, a consumer may rely on the artificial intelligence capabilities of IoT smart home services to learn and adapt environment settings such as temperature according to the routines and preferences of the user. Therefore,

H5a: Habit associated with IoT smart home services has a positive impact on behavioral intention.

H5b: Habit associated with IoT smart home services has a positive impact on use behavior.

Behavior intention

Behavior intention defines the consumer's intention to use the service and is consistent with the UTAUT2 model and its predecessors (UTAUT, Technology Acceptance Model, and Theory of Reasoned Action). The research model in this study proposes that the behavior intention of the consumers of the IoT smart home service will positively influence the behavior of continuing use of the service and its features. Therefore,

H6: Behavioral intention will positively influence use behavior.

Hedonic motivation

Hedonic motivation was introduced in UTAUT2, as a construct representing fun or pleasure derived from using a technology (Venkatesh et al., 2012). The definition as suggested by the authors describe hedonia as a referent in the behavior category rather than orientations, experiences, or functioning, measured at the state rather than the trait level. In the conceptualization presented in Figure 1, well-being is the outcome of inner (self) pursuits that manifest through behavior and are driven by either hedonia or eudaimonia. Hedonic motivation, in this conceptualization, is a driving motive to pursue well-being associated with states of fun or pleasure. In this regard, hedonic motivation coincides with the definition used in UTAUT2, although the model only uses hedonic motivation as predictor of technology adoption. Applied to the context of IoT smart home services, the construct indicates entertainment or fun as derived from the use of IoT smart of home services. Examples include accessing appropriate media content such as movies, shows, music, or online games for entertainment or fun through the use of through smart TVs, tablet, PCs, etc.

In the proposed research model, both adoption and use of the IoT smart home services are influenced by hedonic motivation. Additionally, considering the association of hedonia with positive feelings that accompany the access to material objects one wants, or having the action opportunities one wishes (Deci & Ryan, 2008), hedonic motivation can be considered to have a moderating effect on the relationship between behavior intention and use behavior. The moderating effect of hedonic motivation is evidenced on many aspects of lifestyle where the pursuit of well-being desired by the user may posivitely (if benefits are realized) or negatively (if benefits are not realized) influence the intensity and frequency of continuing use behavior. For example, when functionalities available through IoT smart home services for ambiance control and comfort increases the degree of relaxation achieved by the user, the effect of hedonic motivation on use behavior will be higher. Therefore, we consider the following hypotheses,

H7a: Hedonic motivation associated with IoT smart home services has a positive impact on behavioral intention.

H7b: Hedonic motivation moderates the effect of behavior intention on use behavior, such that the effect will be stronger with higher hedonic motivation.

H7c: Hedonic motivation associated with IoT smart home services has a positive impact on use behavior.

H7d: Hedonic motivation associated with IoT smart home services has a positive impact on well-being.

Use behavior

Use behavior is defined by the individual's use of the IoT smart home service, and implies that the user is actively using features of the service to complete a purpose. For example, the IoT smart home service may include a surveillance feature that continuously streams live feeds from outdoor and indoor cameras to the mobile devices of household members. Here, the feature is in use passively. When a member of the household accesses the live feed to monitor the home and obtain some degree of tranquility, then the user is actively using the service or engaging in use behavior to pursue a state of well-being. Therefore,

H8: Use behavior of IoT smart home services will positively impact well-being.

Eudaimonic motivation

Unlike hedonia, eudaimonic motivation has not been found referenced in IS theory literature. A likely reason is that eudaimonia is conceptually and subjectively broader in meaning. For instance, with hedonia, life pursuits of fun or pleasure are beliefs based on real experiences since everybody experiences feeling of fun or pleasure several times throughout life. With eudaimonia, the life pursuits of meaning, excellence, virtue, growth, development, connection, etc., may never be completed across a person's lifespan. Hedonia represents instant reward with short-term well-being, whereas eudaimonia represents conviction to be rewarded with permanent well-being. Applying the concept of eudaimonic motivation to explain the adoption of technology and thus behavior intention, particularly in the context of IoT smart home services, may seem ambiguous due to the highly subjective nature of eudaimonia. For example, individuals may intend to use the IoT smart home service to monitor and control energy consumption at home, and subsequently generate cost savings representing a utilitarian value lasting the lifetime of the user.

Eudaimonic value is also represented by the use of IoT smart home services to engage in distance learning, gaining personal autonomy, or providing care and assistance to relatives. Here, the use behavior mediates the relationship between eudaimonic motivation and well-being. This implies that the meaning of eudaimonia is highly subjective and individual experiences define eudaimonic motives in distinct ways. The individual contribution of reducing the environmental impact of waste and pollution would be more valued by some users than immediate cost savings, thus representing eudaimonic value that drives the behavior to use the system. This is particularly visible among the population representing milleanials and generation z. In other words, use behavior of IoT smart home services may vary between individuals depending on whether the person's use of the services are driven by eudaimonic motivation or other motives. Therefore, we hypothesize eudaimonic motivation to have a moderating effect on the relationship between use behavior and well-being. Thus,

H9a: Eudaimonic motivation associated with IoT smart home services has a positive impact on use behavior.

H9b: Eudaimonic motivation associated with IoT smart home services has a positive impact on well-being.

H9c: Eudaimonic motivation moderates the effect of use behavior on well-being, such that the effect will be stronger with higher eudaimonic motivation.

4. Methodology

This study investigates the behavior of individuals subscribing to smart home services that use data retrieved from domestic IoT appliances to provide extended functionality at homes. The number of service providers offering a variety of IoT smart home services is currently largest in the United States when compared to other countries in the world. Therefore, the study was conducted targeting users with active subscriptions or have previously subscribed to IoT smart home services in the United States.

4.1. Measurement

To evaluate the theoretical constructs, an online survey was developed targeting users of smart home services in the United States. All of the scales were adapted from prior research. The items used in the questionnaire are included in the Appendix. The scales for the UTAUT2 constructs (i.e., performance expectancy, effort expectancy, social influence, price value, facilitating conditions, habit, and behavioral intention) were adapted from Venkatesh et al. (2012). Hedonia and eudaimonia measures are based on the HEMA scale (Huta & Waterman, 2014), and intended to assess intrinsic motives affecting the level of behavior and well-being. All items were measured on a seven-point likert scale. Use behavior was measured as a formative composite index of both the variety and frequency of IoT smart home services use. A list of eight smart home service categories (i.e., ambiance control, security and safety, energy efficiency, automation, e-health, assisted living, media content consumption, and communications) was provided to respondents who were asked to indicate their usage frequency for each service. The seven-point likert scale ranged from "never" to "many times per day." Age was measured by indication of birthdate and gender was coded with a 0 or 1 dummy variable where 0 represented men.

4.2. Data collection

A pilot test was conducted by distributing the questionnaire to 42 selected respondents that confirmed experience with smart home services. The results demonstrated evidence of validity and reliability of the instrument. Based on the results of the pilot test, one item was dropped, and a final survey was developed and distributed using an Internet-based survey platform. Since the business market for smart home services is still in an early stage, several steps were required to ensure that qualified responses were received. First, the questionnaire was prepared for online distribution with a screening question to ensure that respondents confirmed experience with smart home service subscriptions before proceeding with the remaining questionnaire. Second, the questionnaire was shared through a network of contacts who confirmed experience with smart home services and via Internet discussion forums and social network groups related to smart home service providers and technologies. The vast majority of platforms used to distribute the questionnaire had a user base located in the USA. Follow-up on the distribution channels was performed regularly over twelve weeks, and a total of 260 usable responses was collected. Common method bias (CMB) was tested using the marker-variable technique (Lindell & Whitney, 2001), whereby inserting a theoretically irrelevant marker-variable in the research model resulted in 0.011 (1.1%) of maximum shared variance with other variables. This can be considered low (Johnson, Rosen, & Djurdjevic, 2011), thus suggesting that common method bias was not a concern in our study. The characteristics of the respondents are shown in Table 2.

Table 2. Respondents characteristics

Gender			**Country**		
Male	111	42.69%	USA	257	98.85%
Female	149	57.31%	Other	3	1.15%

Age			**Education**		
18-29	41	15.77%	No schooling completed	4	1.54%
30-39	68	26.15%	High school	95	36.54%
40-49	53	20.38%	Master's degree	101	38.85%
50-59	54	20.77%	Professional degree	34	13.08%
> 60	44	16.92%	Doctorate	26	10.00%

5. Data Analysis and Results

The benefits of applying partial least squares (PLS) in the analysis of topics that have not been tested before is well established (Hair, Ringle, & Sarstedt, 2011; Ke, Liu, Wei, Gu, & Chen, 2009). The technique enables the modeling of latent variables with either reflective or formative indicators and is somewhat indifferent to the types of distribution as opposed to many other analysis techniques that require a normal distribution to render interpretable results (Joseph F. Hair, Hult, Christian, & Marko, 2016). The data collected were tested for normality, and results indicated that the variables were not normally distributed ($p < 0.01$, Kolmogorov–Smirnov's test) (Chin, Marcelin, & Newsted, 2003), ($p < 0.005$, Shapiro-Wilk test) (Mooi & Sarstedt, 2014). Additionally, the model proposed in this study includes formative and reflective constructs, and has not been tested before, thus making PLS an appropriate model for this research. Smart PLS 3.0 was used to test reliability and validity of the measurement model and analyze the structural model (Ringle, Becker, & Wende, 2014).

5.1. Measurement Model

Table 3 and Table 4 present the measurement model results, including reliability, validity, correlations, and factor loadings for the reflective constructs. Construct reliability was tested using composite reliability (CR). The CR results were greater than 0.7 for all constructs (Table 3), suggesting that the scales used were reliable (Hair et al., 2011; Henseler, Ringle, & Sinkovics, 2009; Joseph F. Hair et al., 2016). The average variance extracted (AVE) square root was greater than 0.707, thus establishing convergent validity of the measurement model and, in all cases, higher than the square of the correlations, indicating discriminant validity. The threshold for attaining indicator reliability requires that the loadings should be greater than 0.7 (Hair et al., 2011; Henseler et al., 2009; Joseph F. Hair et al., 2016), which is confirmed in Table 4, and consequently, the reliability indicator is satisfied. Except for one facilitating conditions item that was dropped because of the lower loading and high cross-loadings, all remaining indicators showed loadings (in bold) higher than the cross-loadings, thus supporting discriminant validity. Additionally, all Heterotrait-Monotrait ratios (HTMT) presented in Table 5 are lower than the threshold of 0.9, which provided final confirmation of the discriminant validity of the constructs (Henseler, Ringle, & Sarstedt, 2014). The results, taken together for all the reflective constructs, provided support for the construct reliability of the measurement model, and confirmed that the constructs can be used to test the structural model.

Table 3. Descriptive statistics, correlation, composite reliability (CR), and average variance extracted (AVE)

	Mean	SD	CR	PE	SI	PV	FC	Ha	HM	BI	EM	UB	WB
PE - Performance Expectation	4.517	1.696	0.961	**0.928**									
SI - Social Influence	4.109	1.823	0.962	0.805	**0.946**								
PV - Price Value	4.341	1.707	0.973	0.722	0.732	**0.961**							
FC - Facilitating Conditions	4.595	1.770	0.953	0.734	0.729	0.821	**0.933**						
Ha - Habit	4.044	1.923	0.968	0.766	0.787	0.777	0.725	**0.939**					
HM - Hedonic Motivation	4.511	1.842	0.977	0.710	0.729	0.961	0.651	0.716	**0.936**				
BI - Behaviour Intention	4.539	1.959	0.975	0.734	0.713	0.795	0.811	0.794	0.690	**0.964**			
EM - Eudaimonic Motivation	4.381	1.758	0.969	0.687	0.709	0.726	0.633	0.710	0.853	0.696	**0.928**		
UB - Use Behavior	3.741	1.804	n.a.	0.714	0.697	0.714	0.671	0.780	0.740	0.801	0.738	n.a.	
WB - Wellbeing	4.291	1.813	0.979	0.734	0.749	0.713	0.659	0.777	0.876	0.756	0.859	0.820	**0.899**

Note: Values in diagonal (bold) are the AVE square root; standard deviation (SD).

Table 4. Loadings and cross-loadings

Construct	Item	PE	SI	PV	FC	Ha	HM	BI	EM	WB
PE	PE1	**0.900**	0.709	0.636	0.654	0.683	0.638	0.673	0.597	0.662
	PE2	**0.935**	0.761	0.632	0.636	0.710	0.666	0.660	0.653	0.694
	PE3	**0.932**	0.754	0.721	0.726	0.730	0.665	0.701	0.667	0.679
	PE4	**0.944**	0.762	0.688	0.707	0.720	0.665	0.689	0.632	0.690
SI	SI1	0.774	**0.951**	0.705	0.694	0.746	0.694	0.685	0.658	0.705
	SI2	0.733	**0.950**	0.658	0.654	0.755	0.675	0.647	0.651	0.703
	SI3	0.773	**0.935**	0.709	0.717	0.731	0.697	0.688	0.699	0.715
PV	PV1	0.678	0.697	**0.949**	0.801	0.745	0.655	0.750	0.694	0.669
	PV2	0.694	0.703	**0.972**	0.807	0.747	0.658	0.787	0.683	0.684
	PV3	0.710	0.709	**0.961**	0.757	0.748	0.680	0.752	0.717	0.703
FC	FC2	0.672	0.646	0.746	**0.927**	0.622	0.556	0.705	0.543	0.556

	FC3	0.703	0.705	0.754	**0.948**	0.681	0.616	0.748	0.614	0.619
	FC4	0.679	0.687	0.795	**0.924**	0.719	0.643	0.809	0.610	0.663
Ha	Ha1	0.741	0.748	0.763	0.733	**0.939**	0.675	0.776	0.629	0.726
	Ha2	0.677	0.719	0.685	0.587	**0.929**	0.668	0.683	0.693	0.751
	Ha3	0.701	0.750	0.712	0.644	**0.949**	0.676	0.724	0.684	0.738
	Ha4	0.755	0.738	0.754	0.749	**0.938**	0.671	0.794	0.666	0.708
HM	HM1	0.668	0.707	0.619	0.583	0.702	**0.938**	0.634	0.788	0.837
	HM2	0.684	0.704	0.626	0.599	0.661	**0.948**	0.624	0.797	0.844
	HM3	0.654	0.662	0.623	0.596	0.647	**0.937**	0.623	0.791	0.803
	HM4	0.659	0.675	0.672	0.614	0.677	**0.947**	0.637	0.809	0.816
	HM5	0.670	0.683	0.678	0.624	0.678	**0.933**	0.669	0.811	0.822
	HM6	0.650	0.661	0.666	0.636	0.653	**0.913**	0.685	0.794	0.795
BI	BI1	0.697	0.662	0.756	0.779	0.730	0.643	**0.964**	0.641	0.710
	BI2	0.720	0.711	0.768	0.772	0.794	0.667	**0.965**	0.683	0.752
	BI3	0.705	0.687	0.773	0.795	0.771	0.683	**0.963**	0.688	0.724
EM	EM1	0.648	0.651	0.648	0.621	0.656	0.788	0.666	**0.902**	0.807
	EM2	0.636	0.654	0.682	0.547	0.642	0.785	0.637	**0.936**	0.784
	EM3	0.627	0.652	0.663	0.582	0.663	0.789	0.636	**0.936**	0.799
	EM4	0.645	0.673	0.681	0.597	0.687	0.814	0.651	**0.936**	0.805
	EM5	0.632	0.659	0.698	0.590	0.648	0.781	0.641	**0.932**	0.790
WB	WB1	0.703	0.702	0.660	0.663	0.720	0.841	0.747	0.750	**0.902**
	WB2	0.677	0.702	0.643	0.642	0.723	0.770	0.700	0.787	**0.907**
	WB3	0.609	0.673	0.628	0.538	0.703	0.780	0.627	0.811	**0.897**
	WB4	0.631	0.626	0.598	0.542	0.654	0.809	0.645	0.734	**0.902**
	WB5	0.634	0.677	0.634	0.558	0.726	0.778	0.646	0.811	**0.921**
	WB6	0.667	0.638	0.616	0.595	0.672	0.802	0.670	0.734	**0.892**
	WB7	0.705	0.715	0.688	0.660	0.722	0.793	0.748	0.734	**0.905**
	WB8	0.662	0.682	0.657	0.551	0.715	0.783	0.676	0.811	**0.909**
	WB9	0.658	0.654	0.628	0.580	0.681	0.788	0.676	0.758	**0.901**
	WB10	0.621	0.664	0.608	0.517	0.660	0.735	0.595	0.812	**0.872**
	WB11	0.695	0.672	0.696	0.673	0.711	0.781	0.749	0.757	**0.884**

Note: **PE** - Performance Expectation; **EE** - Effort Expectation; **SI** - Social Influence; **PV** - Price Value; **FC** - Facilitating Conditions; **Ha** - Habit; **BI** - Behavior Intention; **HM** - Hedonic Motivation; **EM** - Eudaimonic Motivation; **WB** - Wellbeing.

Table 5. Heterotrait-Monotrait ratio (HTMT)

Construct	PE	SI	PV	FC	Ha	BI	HM	EM	WB
PE - Performance Expectation									
SI - Social Influence	0.852								
PV - Price Value	0.758	0.770							
FC - Facilitating Conditions	0.783	0.779	0.870						
Ha - Habit	0.804	0.830	0.811	0.765					
BI - Behaviour Intention	0.769	0.748	0.828	0.857	0.826				
HM - Hedonic Motivation	0.740	0.762	0.717	0.683	0.743	0.713			
EM - Eudaimonic Motivation	0.720	0.745	0.758	0.669	0.742	0.724	0.883		
WB - Well-being	0.764	0.781	0.738	0.690	0.805	0.780	0.899	0.887	

Use behavior is a formative construct, and its indicators were evaluated for multicollinearity, sign of weights, and significance. Outer weights and the variance inflation factor (VIF) are presented in Table 6. All VIF values are in the range 2.5 - 4.7, thus under the threshold of 5 (Hair et al., 2011) suggesting multicollinearity is not an issue. Not all the indicators had identical statistical significance, but the signs of the outer weights are all positive, and the outer loadings are higher than 0.5. This confirmed that the use behavior construct could be used to test the structural model.

Table 6. Multicollinearity of the formative construct

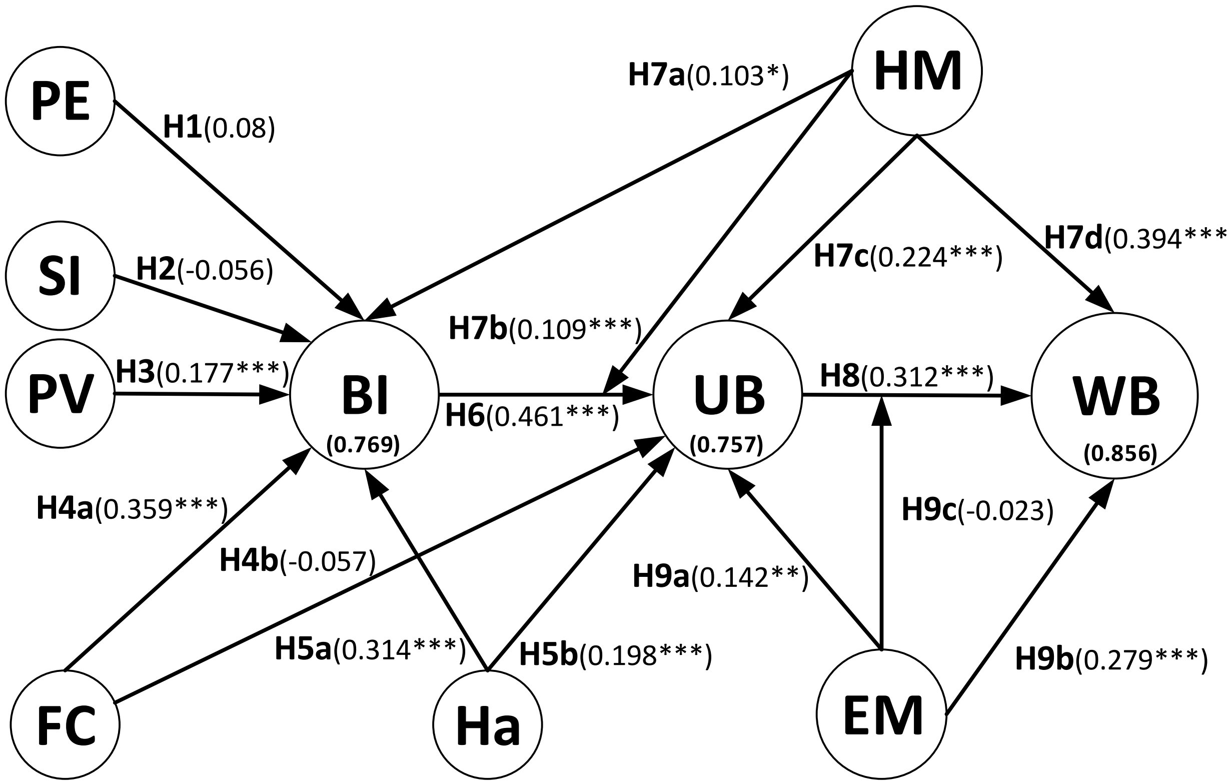
Latent variable	Measurement variable	VIF	Outer Weights	Outer Loadings
UB	UB1	3.362	0.195**	0.879***
	UB2	2.908	0.142**	0.824***
	UB3	4.700	0.091	0.881***
	UB4	4.177	0.111	0.874***
	UB5	3.810	0.067	0.850***
	UB6	2.551	0.098*	0.748***
	UB7	3.767	0.240***	0.891***
	UB8	3.713	0.217***	0.879***

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

5.2. Structural model

Before evaluating the structural model, it is necessary to conduct a verification for the existence of multicollinearity. The computed variance inflation factors (VIFs) for the constructs in the model varied in the range from 1.020 to 4.348, suggesting that multicollinearity was not an issue for the study. The levels of statistical significance of the hypothesized constructs were tested by using bootstrapping with 5000 resamples. The results of the structural model are presented in *Note*: ***PE*** - Performance Expectation; **SI** - Social Influence; **PV** - Price Value; **FC** – Facilitating Conditions; **Ha** - Habit; **BI** - Behavior Intention; **HM** - Hedonic Motivation; **EM** - Eudaimonic Motivation; **UB** – Use Behavior; **WB** - Wellbeing.

Figure *3* along with variations explained, and the path coefficients.



Note: **PE** - Performance Expectation; **SI** - Social Influence; **PV** - Price Value; **FC** – Facilitating Conditions; **Ha** - Habit; **BI** - Behavior Intention; **HM** - Hedonic Motivation; **EM** - Eudaimonic Motivation; **UB** – Use Behavior; **WB** - Wellbeing.

Figure 3. Structural model evaluation results

The model explains 76.9% variation in behavior intention to adopt IoT smart home services. Performance expectation (PE) ($\hat{\beta}$= 0.08; p > 0.1) and social influence (SI) ($\hat{\beta}$ = -0.056; p > 0.1) are not statistically significant in explaining behavior intention; therefore, H1 and H2 are not confirmed. The relationship between price value (PV) ($\hat{\beta}$ = 0.177; p < 0.01) and behavior intention (BI) is statistically significant, thus confirming H3. The effects of facilitating conditions (FC) ($\hat{\beta}$ = 0.359; p < 0.01), habit (Ha) ($\hat{\beta}$ = 0.314; p < 0.01), and hedonic motivation (HM) ($\hat{\beta}$= 0.103; p < 0.1) on the behavior intention to adopt IoT smart home services (BI) are statistically significant; thus H4a, H5a, and H7a are confirmed.

The model explains 75.7% variation in use behavior of IoT smart home services. Facilitating conditions construct (FC) ($\hat{\beta}$ = -0.057; p > 0.1) is not statistically significant, so H4b is not confirmed. Habit (Ha) ($\hat{\beta}$ = 0.198; p < 0.01), behavior intention (BI) ($\hat{\beta}$ = 0.461; p < 0.01), hedonic motivation (HM) ($\hat{\beta}$ = 0.224; p < 0.01), moderation effect of HM on BI ($\hat{\beta}$ = 0.109; p < 0.01), and eudaimonic motivation (EM) ($\hat{\beta}$ = 0.142; p < 0.05) are statistically significant. Consequently, H5b, H6, H7b, H7c, and H9a are confirmed.

Finally, the model explains 85.6% of the variation in well-being. Hedonic motivation (HM) ($\hat{\beta}$ = 0.394; p < 0.01), use behavior (UB) ($\hat{\beta}$ = 0.312; p < 0.01) and eudaimonic motivation (EM) ($\hat{\beta}$ = 0.279; p < 0.01) are statistically significant. Hence, H7d, H8, and H9b are supported. The moderating effect of eudaimonic motivation (EM) on the relationship between use behavior and well-being ($\hat{\beta}$ = -0.023; p > 0.1) is not statistically significant. Therefore, H9c is not confirmed.

The results indicate that hedonic motivation positively moderates the positive relationship between the behavior intention to adopt IoT smart home services and the associated use behavior. As hedonic motivation increases, the slope between behavior intention and use behavior of IoT smart home services also increases (Figure 4). The plot in Figure 4 suggests that, although the intention to adopt IoT smart home services is positively associated with the use behavior of such services, this relationship is positively reinforced when the degree of hedonic motivation is high.

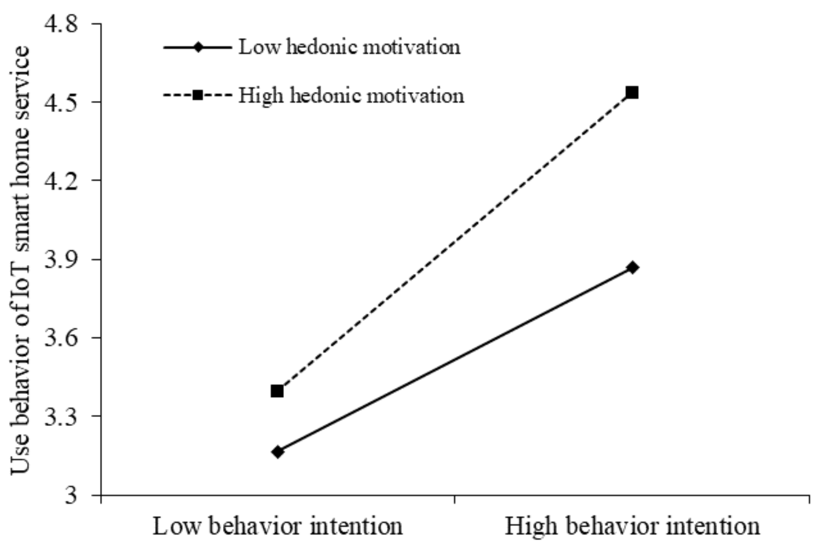


Figure 4. Moderation effect of hedonic motivation between behavior intention and use behavior

6. Discussion

We propose a model that combines UTAUT2 with the conceptualization of intrinsic motivation to evaluate the impact of IoT smart home services on well-being. Construct relationships are established based on hedonic and eudaimonic motives of individuals in the use of smart home services.

In the context of the IoT smart home services, our results did not indicate that performance expectation or social influence were drivers for the adoption of IoT smart home services. Although this finding contradicts the UTAUT model, it is not entirely surprising as UTAUT and similar models of technology adoption associate the advantages of technology to its use in daily lifes (Macedo, 2017; Shaw, Ellis, & Ziegler, 2018). In contrast, performance expectancy is inherent in smart home services, as they are designed to execute activities according to the specifications of the user and with minimal user involvement. Additionally, service providers play a crucial role in ensuring that performance expectations of smart home services are met. Many smart home services provide expected performance as per specifications, and include remote monitoring that allows the service provider to act in case of services interruptions. Service providers also typically offer consumers direct communication lines for support and assistance. Smart home services are designed to be universal and non-discriminant of consumer's technology self-efficacy, and this may explain why social influence is not a driver for the adoption of IoT smart home services.

The study results indicated that price value was significant in explaining the intention to use IoT smart home services. This finding is consistent with Y. Kim et al. (2017). Thus, a consumer perceiving higher value in the smart home service (for example, perceived benefits of reducing energy waste, having the home protected, or creating more comfort at home) is more willing to expend the monetary costs associated with the service (Hsu & Lin, 2016). Our study found that facilitating conditions influenced the behavior intention to use the smart home services. However, unlike the UTAUT model (Baptista & Oliveira, 2016), it was not found to influence use behavior. It may be that, even though the consumer has intentions to use smart home services, barriers such as difficulties in learning to use the service may inhibit the actual use of the service. Our results also confirmed habit to influence both intention and use of smart home services. This suggests that incremental use of IoT smart home services are driven by improvements in the quality of life and well-being as perceived by the user.

One of the objectives of this study was to investigate the role of hedonic and eudaimonic motives on behavior and well-being. Past studies have found hedonic motivation to be a strong predictor of the intention to use and adopt technologies in households (Brown & Venkatesh, 2005) and multimotive information systems (Lowry, Gaskin, Twyman, Hammer, & Roberts, 2013; Lowry, Gaskin, & Moody, 2014). Our study also found a similar conclusion in the context of the IoT smart home services, where hedonic motivation is shown to be a predictor of behavior intention and use behavior. Typically, service providers of IoT smart home services provide a technology ecosystem targeting a specific service domain (security, energy management, lifestyle support, etc.), which limits the set of smart home functionalities available to the consumer. For instance, a subscriber to an IoT smart home service package for home security may receive intruder detection and surveillance features, while entertainment or comfort features would not be part of this ecosystem. For these additional features, the consumer would need to subscribe to supplementary service packages either from the same provider or a different one. Although the hedonic construct of UTAUT posits the role of enjoyments in technology use, our findings suggest that the influence of this construct on smart home technology use is context-dependent (McLean & Osei-Frimpong, 2019). In other words, hedonic motivation to use a specific smart home technology is dependent on how it generates the feeling of enjoyment or pleasure. Our study also shows that the moderating effects of hedonic motivation indicating that it conditions the intention to use smart home services and the use behavior. As hypothesized, hedonic motivation has a direct impact on well-being in the context of specific smart home services selected and used by the consumer.

Eudaimonia is grounded on individual life experiences, values, and beliefs, and constitutes a more subjective experience. Thus, eudaimonic motivation is harder to model and measure than hedonic motivation and unlikely to be a strong predictor of intention to use or use behavior of technology in the consumer context. Nevertheless, the HEMA scale (Bujacz, Vittersø, Huta, & Kaczmarek, 2014) enabled us to measure the effects of eudaimonic motivation in the use of smart home services and well-being. Our results suggest that eudaimonic motivation is less significant in the consumer's intentions to use smart home services when compared to hedonic motivation. It also has a lesser effect on well-being. This finding is consistent with the study by L. W. Henderson et al. (2013) that showed hedonia as a better predictor for life satisfaction than eudaimonia. The likely explanation is that the latter motivates behavior towards pursing personal growth or change, and therefore, unrelated to satisfaction with the status quo. The evidence to this is the insignificant moderating effect of eudaimonic motivation on the relationship between use behavior and well-being. However, the direct effect of use behavior on well-being is evident in our study results. Thus, our proposed model signifies a relationship between the adoption and use of IoT smart home services and individual well-being.

6.1. Impacts on research and practice

The study consolidates existing theory on the adoption and use of technology with the conceptual model of well-being, and offers a multitude of insights for research and practice. Our findings contribute to the body of knowledge on the role of technology on well-being, in particular the application of UTAUT2 to explain the impact of intrinsic motivations on behavior pursuits around IoT smart home services. For researchers, the study provides a consolidated model that explains intrinsic motivations to use smart home services and its effect on well-being. In addition, the research unveiled the role of eudaimonic motivation and the moderating effect of hedonic motivation on use behavior involving smart home services.

From a practitioner viewpoint, the study presents insights for technology companies, service providers, government agencies, and regulatory bodies. Technology companies and service providers in the smart home marketplace develop portfolios of services with the goal of providing quick and tangible benefits and gratification to consumers who use the services. The services are thus perceived by the consumer to be of hedonic value (Luo & Remus, 2014). Since eudaimonia does not manifest as tangible benefits or immediate gratification, business strategies to explore and monetize on such values may be harder to develop. However, carefully targeted strategies that align with eudaimonic interests may prove valuable to the organization in the long run. For example, service providers may develop and promote innovative services targeting the heudonic needs of people suffering from mobility limitations, thus allowing them greater independence, autonomy, and control over activities at home. However, developing a strategy that targets long-term personal development of the disabled and sustainable social connections would serve the long-term eudaimonic interests and resulting customer loyalty. The price value for such services condition the continued use and reliance on the services, thus enabling further growth in the market sector.

Government agencies and regulators are bound to address the needs of citizens and increasingly offer higher quality of public services through the use of IoT smart devices. Public services such as energy, water, sewer, and garbage collection represent a comfort value for citizens. The quality and availability of enhanced public services reflect in the higher quality of life and well-being. IoT devices play a major role in the modernization of public services. They provide significant improvements in how data on the consumption and use of public resources are gathered and disseminated. Although upgrading public infrastructure to integrated IoT technologies may incur higher costs to the government and homeowners, our study suggests that the quality and availability of public services enhanced through the use of IoT smart home services may reflect in the higher quality of life and well-being. While IoT induced policy changes are inevitable for comprehensive public service enhancements, they may also be controversial and subject to public opposition (for e.g., retrofitting older homes with IoT technology may not be in the interest of the homeowner). Therefore creating policies that aim to promote citizen use of IoT smart home services (e.g., implementing smart sensors to monitor real-time energy use, water usage, and environmental impact) should include strategies that articulate the eudaimonic value to the society, such as life preservation, sustainability, and greater overall well-being of those impacted by policy changes.

The demand and use of IoT based security products and services have increased exponentially in the recent years (Park et al., 2018). However, incidents of cyber hacking resulting in data falling in the wrong hands and selling of personal data by IoT companies have also increased (Li, Da Xu, & Zhao, 2015; Whitmore, Agarwal, & Da Xu, 2015). Although prior studies have indicated that perceived concerns of privacy and security have no effect on perceived usefulness (Park et al., 2018) and negatively affect the attitude (Yang, Lee, & Zo, 2017) towards smart home services, growing concerns may differentiate use behavior and eventually, the uptake of smart home services and products (Balta-Ozkan, Davidson, Bicket, & Whitmarsh, 2013). More research is warranted to shed light on the impact of IoT privacy and security on psychological well-being.

6.2. Limitations and future research

Providers of smart home ecosystems and platforms are still low in number, and related services limited in functionality. Marketing strategies of many smart home service providers target selling products rather than smart home services. In many cases, purchasing IoT devices and configuring smart home services are the responsibility of the consumer, whereas the service provider only offers an Internet endpoint to receive data generated by the smart devices. At best, an information dashboard is available from the service provider, while the maintenance and continued operation of the IoT devices and smart home services become the burden of the consumer. The respondents in our study were from the United States, where there is a greater diversity of service providers operating in the smart home services market and the IoT ecosystem is more advanced than the rest of the world. All of these factors may have an implication on the generalization of conclusions presented in the study.

Another limitation of our study is the effect of CMB. Since smart home services are relative new and based on IoT technologies that have not adequately matured, the respondents of our study would likely have been early adopters of IoT technology and services with a positive outlook towards its benefits. Our study was designed to be exploratory in nature, and its objective was to assess the impact of IoT smart home services on well-being. Therefore, although we tested for CMB and found no reason for concern, we encourage future research to develop a more rigorous design using different objective measures aimed at reducing method and measurement biases and to rule out any imbalance in the dataset due to early adopters.

Our study used UTAUT2 to explain the intentions to use smart home services and related use behavior. The analysis results showed that some constructs considered relevant to technology adoption (e.g., performance expectancy, effort expectancy, and social influence) did not explain the adoption of IoT smart home services. This may be due to the fact that users of IoT smart home technology have a more practical reference point with regard to its role in supporting their activities, whereas the adoption of services are a more intrinsic composition depending on whether the use of such services fulfill a behavioral pursuit. Additionally, published literature portrays well-being under varying conceptualizations based on differing philosophical roots. There is much debate on whether the cultivation of intellectual and moral virtues is best judged externally by others than the agents (in our case, the study participants) themselves (Kristjánsson, 2018). Given the large size of our study sample, we replied on self-reporting of eudaimonic motivations. We acknowledge this as a potential limitation of our study and call upon future research to enrich the findings of this study by including objective measurements of eudaimonic motivations.

7. Conclusion

This study investigated the impact of IoT smart home services on well-being, and accessed the direct effects of the individual's motivations for well-being and the indirect effects of hedonic and eudaimonic motives. We explored the determinants for the adoption and use of emerging IoT smart home services based on the proven robustness of the UTAUT2 framework while combining it with the conceptual model of well-being derived from published literature. We developed a measurement instrument based on which data was collected using an online survey of 260 IoT smart home service users in the United States. The research model was empirically validated and the analysis of results found a direct relationship between the use of IoT smart home services and well-being. The results also confirmed the direct effects of hedonic motives and eudaimonic motives on well-being, as well as their indirect effects on the use of IoT smart home services. The results indicated that, although facilitating conditions, habits of the users, and price value of smart home services are stronger drivers than hedonic motivation, the latter directly influenced the intention to use smart home services and moderated its relationship with use behavior. The study found that hedonic motivation acted as a positive reinforcement to all stages of behavior intentions and continuing use of smart home services proposed in the research model. In comparison, the results indicated that eudaimonic motivation had a weaker influence on use behavior and well-being. The research showed that in assessing the use of IoT based smart home services, a scientific approach that takes into consideration the subjective nature of hedonic and eudaimonic perceptions based on the individual's intrinsic motivations is more meaningful in providing valuable insights to research and practice.

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Appendix – Survey items

Performance Expectancy adapted from Venkatesh et al. (2012)
PE1 I find IoT Smart Home service useful in my household.
PE2 Using IoT Smart Home service increases my chances of achieving things that are important to me.
PE3 Using IoT Smart Home service helps me to accomplish domestic tasks more quickly.
PE4 Using IoT Smart Home service increases my productivity.

Social Influence adapted from Venkatesh et al. (2012)
SI1 People who are important to me think that I should use the IoT smart home service.
SI2 People who influence my behavior think that I should use the IoT smart home service.
SI3 People whose opinions I value prefer that I use the IoT smart home service.

Facilitating Conditions adapted from Venkatesh et al. (2012)
FC1 I have the resources necessary to use the IoT smart home service.
FC2 I have the knowledge necessary to use the IoT smart home service.
FC3 The IoT smart home service is compatible with the technologies that I use.
FC4 I can get help from others when I have difficulties using the IoT smart home service.

Price Value adapted from Venkatesh et al. (2012)
PV1 The IoT smart home service is reasonably priced.
PV2 The IoT smart home service is a good value for the money.
PV3 At the current price, the IoT smart home service provides good value.

Habit adapted from Venkatesh et al. (2012)
Ha1 The use of the IoT smart home service has become a habit for me.
Ha2 I am addicted to using the IoT smart home service.
Ha3 I must use the IoT smart home service.
Ha4 Using the IoT smart home service has become natural to me.

Hedonic Motivation adapted from Huta and Waterman (2014)
I use the IoT smart home service in my home when I start an activity with the intention of:
HM1 Seeking relaxation.
HM2 Seeking pleasure.
HM3 Seeking enjoyment.
HM4 Seeking to take it easy.
HM5 Seeking fun.
HM6 Seeking to make things comfortable.

Eudaimonic Motivation adapted from Huta and Waterman (2014)
I use the IoT smart home service in my home activities when I am:
EM1 Seeking to develop a skill, learn, or gain insight into something.
EM2 Seeking to do what I believe in.

EM3 Seeking to pursue excellence or a personal ideal.
EM4 Seeking to use the best in myself.
EM5 Seeking to contribute to others or the surrounding world.

Behavior Intention adapted from Venkatesh et al. (2012)
BI1 I intend to continue using the IoT smart home service in the future.
BI2 I will always try to use the IoT smart home service in my daily life.
BI3 I plan to continue to use the IoT smart home service frequently.

Use Behavior adapted from Venkatesh et al. (2012)
Please choose your usage frequency for each of the following features of the IoT smart home service at your home:
a) ambiance control (temperature, lighting, sound, etc.)
b) security and safety (video surveillance, presence detection, fire alarm, gas leak alarm, flood alarm, etc.)
c) energy efficiency (reduce energy waste, schedule use of appliances outside tariff peak hours, etc.)
d) automation (allow the service to learn my preferences by tracking my movements and activity schedules at home)
f) e-health (collecting health data from wrist bands or other sensors to monitor health status or telemedicine purposes)
g) assisted living (allow autonomy or independence at overcoming a disability or handicap in activities at home)
h) media content consumption (distribute digital media through devices at home or access online music, movies, games, etc.)
i) communications (establish a remote connection to home, connect to social platforms, shop or perform online transactions)
Note: Frequency ranged from “never” to “many times per day.”

Well-Being adapted from Huta and Waterman (2014)
All things considered, to which degree has the IoT Smart Home service been useful in your domestic routines when you're:
WB1 Seeking relaxation?
WB2 Seeking to develop a skill, learn, or gain insight into something?
WB3 Seeking to do what you believe in?
WB4 Seeking pleasure?
WB5 Seeking to pursue excellence or a personal ideal?
WB6 Seeking enjoyment?
WB7 Seeking to take it easy?
WB8 Seeking to use the best in yourself?
WB9 Seeking fun?
WB10 Seeking to contribute to others or the surrounding world?
WB11 Seeking to make things comfortable?