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Examining User Acceptance and Adoption of the Internet of Things

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Abstract

The Internet of Things (IoT) promises a new technological paradigm that can offer a number of innovative applications and services targeting different scopes of adoption. The full potential impact of the IoT is enormous due to its pervasive nature and the rapid improvement of enabling technologies. Taking lessons from information technology and systems in their early stages, a low degree of user acceptance would hinder the progress of IoT implementation. Studies of the IoT from the user perspective mainly investigated factors influencing acceptance and use of a specific service or application. A comprehensive view of users' attitude toward the IoT platform may offer further insights. Drawing upon the Diffusion of Innovation Theory and the Technology Acceptance Model, this study examined six potential determinants of users' adoption of the IoT platform and tested two potential psychological outcomes. Using data collected from 615 potential users and analysing with structural equation modelling techniques, the results and findings of this study contribute to facilitating understandings of IoT acceptance and adoption.

Keywords: Internet of Things, Technology acceptance, Diffusion of Innovation, Structural equation modelling

1. INTRODUCTION

The Internet of Things (IoT) promises a new technological paradigm, by connecting anything and anyone at any time and any place, using any path/network and any service (Baldini, Botterman, Neisse, & Tallacchini, 2016; Guillemin & Friess, 2009; Man, Na, & Kit, 2015; UK Research Council, 2013). The IoT vision is that of a *"smart world"* which is equipped with sensing technologies and smart components (Lu, Papagiannidis, & Alamanos, 2018). The IoT features Web 3.0, which involves users much more deeply than its predecessor, namely Web 2.0, as they and their immediate physical environment are more heavily involved with the technology in ways that go far beyond content creation and sharing (Kreps & Kimppa, 2015). Not surprisingly, such a bold vision has captured the imagination and attention of both academics and practitioners, as the IoT could underpin innovative services and applications (Lu et al., 2018). The IoT is expected to have a significant impact on individuals, businesses, and policy as societal and business models will be challenged, and new services introduced (Shin, 2014; Stankovic, 2014).

IoT can offer a number of innovative applications and services targeting different scopes of adoption, such as the smart city that integrates multiple technologies at infrastructural level and smart home that applies at the individual level (Leong, Ping, & Muthuveloo, 2017; Lu et al., 2018; Marikyan, Papagiannidis, & Alamanos, 2020). However, most of the early IoT products were developed by merely equipping existing objects with sensors or tags, aimed at facilitating the collection, processing and management of information (Lu et al., 2018). Despite the fact that only a small number of applications and services is currently available to individuals, the full potential impact of the IoT is enormous due to its pervasive nature and the rapid improvement of enabling technologies (Atzori, Iera, & Morabito, 2010; Shin, 2014). One of the future trends of IoT technologies is becoming user-oriented, which will further facilitate the developmental activities and satisfy the diverse needs of users (Lee & Lee, 2015; Shin, 2014; Sundmaeker, Guillemin, Friess, & Woelffle, 2010; Vermesan et al., 2015). Given that IoT technologies and services are steadily progressing and reaching mainstream markets, it is high time to examine the IoT from the perspective of users.

The viability and prospects of IoT applications and services are largely determined by the market demand and user acceptance (Kim & Kim, 2016). Taking lessons from information technology and systems (IT/IS) in their early stages, a low degree of user acceptance would hinder the progress IoT implementation (Kim & Kim, 2016). Prior studies from the user perspective mainly investigated factors influencing acceptance and use regarding a specific IoT service or application, and provided suggestions for practitioners in formulating business strategies to attract better adoption, e.g., (Bao, Chong, Ooi, & Lin, 2014; Chong, Liu, Luo, & Keng-Boon, 2015; Gao & Bai, 2014). Although previous studies on IoT acceptance provided valuable insights, solely adapting mainstream information system management (MIS) theories for different contexts has limitations in providing comprehensive views of the IoT platform. Besides, one recent article investigated the IoT as a platform and studied the spillover effect from its predecessor, i.e., the Internet platform, and reported significant influences of emotional reactions and psychological outcomes of Internet use on IoT acceptance (Lu, Papagiannidis, & Alamanos, 2021). Following the above, the second objective of this study is to examine factors influencing user acceptance of the IoT as a technological paradigm.

Studies on user acceptance and adoption have sufficiently explored influential factors adapted from a number of MIS theories and have tested their effects on the users' behaviours of technology use (Venkatesh, 2021). Also, the majority of IoT acceptance and adoption studies were conducted under a specified research context or targeting a specific IoT service or application. As such, a comprehensive view of users' attitude toward the IoT platform may offer further insights. In addition to the widely employed technology acceptance theories, the Innovation Diffusion Theory (IDT) (Rogers, 1962; Rogers, 1995), which investigates the process of diffusion, may offer valuable insights into understanding IoT adoption. Given so, incorporating and testing factors from technology adoption theories potentially contribute to facilitating understandings of IoT acceptance and adoption.

The following sections proceeds to discuss the hypotheses and theoretical framework put forward, the methodology and analysis approach used, statistical results and findings, as well as discussion and conclusions.

2. HYPOTHESES DEVELOPMENT AND RESEARCH FRAMEWORK

2.1 IoT Acceptance and Adoption

The various antecedents of individual, technology and environmental characteristics as well as the consequences of use are typically studies in technology adoption literature (Venkatesh, 2021). Furthermore, studies of the IoT from the user perspective largely focus on exploring and examining potential factors influencing users' acceptance of one given IoT application or service. The majority of the current studies were conducted within a specified research context or targeting a specific IoT service, e.g. smart home (Bao et al., 2014; Kim, Park, & Choi, 2017; Marikyan et al., 2020; Park, Cho, Han, & Kwon, 2017), smart healthcare/eHealth (Arfi, Nasr, Khvatova, & Ben Zaied, 2021; Arfi, Nasr, Kondrateva, & Hikkerova, 2021; Karahoca, Karahoca, & Aksöz, 2017; Martínez-Caro, Cegarra-Navarro, García-Pérez, & Fait, 2018; Pal, Funilkul, Charoenkitkarn, & Kanthamanon, 2018), autonomous vehicles (Manfreda, Ljubi, & Groznik, 2021; Yuen, Cai, Qi, & Wang, 2021), and smart city (Leong et al., 2017).

The majority of IoT acceptance and adoption studies were drawn upon technology acceptance theories such as the Technology Acceptance Model (TAM) (Davis, Bagozzi, & Warshaw, 1989), the Unified Theory of Acceptance and Use of Technology (Venkatesh, Morris, Davis, & Davis, 2003), the Theory of Planned Behaviour (Ajzen, 1991), etc. Also, the most commonly tested dependent variable is behavioural intention, which indicates the individual's readiness to perform a given behaviour (Davis et al., 1989; Tscherning, 2012; Venkatesh, 2021). Evidence from previous studies supported that the two fundamental constructs of TAM, i.e., perceived usefulness and perceived ease of use, significantly and positively determine the users' intention of using IoT applications and services (Bao et al., 2014; Gao & Bai, 2014; Jang & Yu, 2017; Liew et al., 2017; Mital, Chang, Choudhary, Papa, & Pani, 2017; Park et al., 2017).

IDT is one of the most influential theories in understanding technological evolution, postulated that individuals' degree of willingness of adoption is contigent on the individuals' perceived characteristics of the target innovation (Marikyan et al., 2020; Rogers, 1995; Tornatzky & Klein, 1982). More specifically, IDT explored and developed a comprehensive set of attributes of innovation that significantly determine the adoption (Rogers, 1962). This set of attributes has been further revised to six perceived characteristics of innovating, i.e. relative advantage, complexity, compatibility, result demonstrability, visibility, and trialability (Moore & Benbasat, 1991; Rogers, 1983). The users appraise the innovation characteristics after utilisation and reconsider the decision of continuous usage (Marikyan et al., 2020; Rogers, 1995). This article aims to first test the effects of innovation characteristics on user adoption of the IoT platform. Six hypotheses are put forward as follows.

First of all, relative advantage is a leading factor that determines the users' intention of adoption (Abu-Khadra & Ziadat, 2012), referring to *"the degree to which an innovation is perceived as being better than the idea it supersedes"* (Rogers, 1983). The *"advantage"* is often expressed in terms of economic profitability, social prestige, convenience, and satisfaction (Karahoca et al., 2017; Rogers, 1983). However, whether an innovation is objectively advantageous has limited influence on the users' adoption; instead, the individual's perception of the advantages determines the rate of adoption (Rogers, 1983). Perceived usefulness directly describes the perceived utilitarian value and functionalities of new technology, which is defined as the degree to which an individual believes that using the technology might enhance their performance in completing tasks (Davis, 1989; Davis et al., 1989). This study employed perceived usefulness in testing IoT adoption intention.

An empirical study on the acceptance of smart lockers suggested that relative advantage has positivi effects on the users' attitude toward adoption (Tsai & Tiwasing, 2021). Beaides, perceived advantage was also reported having positive invluence on the users' perceived usefulness, perceived ease of use, and behavioural intention of smart healthcare (Karahoca et al., 2017). Perceived usefulness was also reported as having positive effects on the users' attitude (Karahoca et al., 2017; Park et al., 2017), behavioural intention (Bao et al., 2014; Gao & Bai, 2014; Liew et al., 2017; Mital et al., 2017; Park et al., 2017), reuse intention (Jang & Yu, 2017), and satisfaction (Martínez-Caro et al., 2018) of using the IoT. With the aim of investigating the users' intention toward adopting the IoT, this study hypothesised that

H1a: Perceived usefulness is positively correlated with users' behavioural intention of using the IoT.

Complexity refers to *"the degree to which an innovation is perceived as relatively difficult to understand and use"* (Rogers, 1983), while perceived ease of use is defined as the degree to which an innovation is perceived to be easy to learn and use (Moore & Benbasat, 1991). These two constructs have a resemblance in concept (Moore & Benbasat, 1996; Venkatesh et al., 2003). Fundamentally, an innovation that is perceived to be less complicated is more likely to be accepted and adopted (Davis et al., 1989; Rogers, 1995). The effect of perceived ease of use on IoT acceptance and adoption is arguable. The majority of studies have reported positive effects of perceived ease of use on users' attitudes toward IoT, e.g., (Gao & Bai, 2014; Liew et al., 2017; Mital et al., 2017; Park et al., 2017). However, the study of (Bao et al., 2014) did not show a significant effect while the studies of (Karahoca et al., 2017; Tsai & Tiwasing, 2021) reported negative effects of complexity/perceived ease of use on users' attitudes and intentions of adopting IoT service. This study proposes to examine the role of perceived ease of use and proposes a positive effect.

H1b: Perceived ease of use is positively correlated with users' behavioural intention of using the IoT.

The third perceived characteristic of innovation, compatibility, refers to *"the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters"* (Rogers, 1983). A high degree of compatibility implies that an innovation is less uncertain to its' potential adopters (Rogers, 1983). Ensuring the compatibility between IoT products is critical since IoT-based services are enabled by connecting many smart objects into the network (Shin, Park, & Lee, 2018). For instance, smart home services usually require connection and communication between various home appliances (Shin et al., 2018; Tsai & Tiwasing, 2021) and benefits of autonomous vihicles should be compatible with users' green lifestyle and special travel needs (Yuen et al., 2021). Previous studies reported that compatibility is one of the most influential characteristics on IoT acceptance and adoption, e.g., (Bao et al., 2014; Hubert et al., 2018; Karahoca et al., 2017; Park et al., 2017; Shin et al., 2018; Tsai & Tiwasing, 2021; Yuen et al., 2021), etc.

H1c: Compatibility is positively correlated with users' behavioural intention of using the IoT.

Observability in IDT has been separated into result demonstrability and visibility (Moore & Benbasat, 1991). Result demonstrability refers to the degree to which the results of using an innovation are visible and communicable to the others (Moore & Benbasat, 1991, 1996; Rogers, 1983). It also describes the tangibility of the results of using the innovation (Moore & Benbasat, 1991). Even an effective IS/IT could fail to gain acceptance and adoption if the users cannot attribute their performance to using it (Rogers, 1983; Venkatesh & Davis, 2000). The study of (Hubert et al., 2018) indicated that the effects of result demonstrability were positive on perceived ease of use, negative on perceived usefulness, and not significant for behavioural intention of adopting the smart home system. A study of autonomous vehicle adoption reported that result demonstrability positively influences perceived usefulness and perceived ease of use (Yuen et al., 2021). This study proposes to test the effect of result demonstrability on IoT adoption decisions.

H1d: Result demonstrability is positively correlated with users' behavioural intention of using the IoT.

Visibility describes the degree to which an IS/IT is apparent to the sense of sight (Moore & Benbasat, 1991, 1996; Rogers, 1983), and does not necessarily require communication between potential users. Visibility was suggested to be influential in persuading potential users to try the innovation (Agarwal & Prasad, 1997). The finding of (Chuah et al., 2016; Yuen et al., 2021) suggested that visibility positively affects the adoption of IoT applications. However, the study by (Hubert et al., 2018) reported a non-significant effect of visibility on smart home adoption. Many IoT products, such as wearable devices for smart healthcare, smart transportation services, and smart security products that are distributed in public spaces, are noticeable for the potential users (Lu et al., 2018). However, IoT products distributed in private spaces may not be visible to others. This study expects that visibility will be an influential factor in enhancing adoption of the IoT paradigm.

H1e: Visibility is positively correlated with users' behavioural intention of using the IoT.

Lastly, trialability is defined as *"the degree to which an innovation may be experimented with on a limited basis"* (Rogers, 1983), which describes the possibility of trying out or using an innovation before adoption (Moore & Benbasat, 1991, 1996). A high degree of trialability of innovation can decrease the perceived uncertainty for the potential adopters, which further enhances the adoption and use (Dutta & Omolayole, 2016; Rogers, 1983). The study of (Yuen et al., 2021) suggested that trialability positively influences users' perceived usefulness and ease of use of autonomous vehicles. Although very few studies have examined the effects of trialability, it is an important component in the process of technology adoption (Karahoca et al., 2017; Mohamad Hsbollah, Kamil, & Idris, 2009).

H1f: Trialability is positively correlated with users' behavioural intention of using the IoT.

2.2 Internet of Things and Well-being

Well-being refers to the users' need fulfilment and quality of life enhancement by using the IoT (Lu, Papagiannidis, & Alamanos, 2019; Partala & Saari, 2015). IoT will bring about many benefits in the users' daily life, such as improving convenience and promoting well-being (Marikyan, Papagiannidis, & Alamanos, 2018; Wang, McGill, & Klobas, 2018). Also, improving the users' psychological well-being is a long-term objective of smart technologies (Marikyan et al., 2018). Among the wide range of IoT-based services, IoT healthcare would largely benefit the users and enhance their well-being by monitoring health remotely, thus reducing pointless hospitalisation and lessening expenses in human services (Martínez-Caro et al., 2018; Mital et al., 2017; Papa, Mital, Pisano, & Del Giudice, 2018). Smart buildings and smart cities that have massively distributed IoT-enabled sensors can monitor the surrounding environment. thus creating a better living condition for the citizens, ideally benefiting their health and well-being (Spaceti, 2017). Broadly speaking, IoT services and products can positively influence the users' well-being.

H2: Using the IoT is positively correlated with users' degree of well-being.

2.3 Internet of Things and Perceived Value

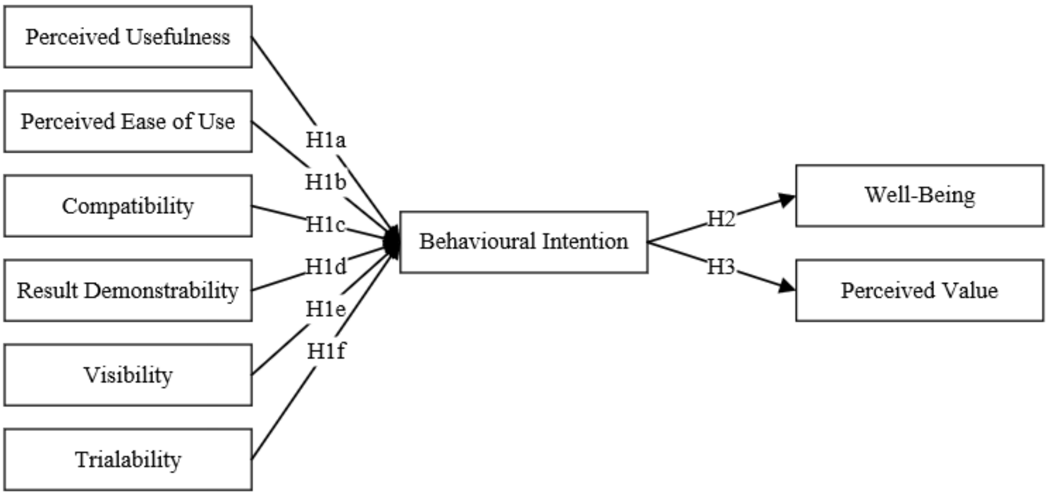
Taking into account that IS/IT plays a critical role in people's daily life nowadays, it is believed to possess value for individuals. MIS studies proposed a number of constructs to represent different values affecting technology acceptance and use, such as performance/utilitarian value (e.g. PU and PEOU), hedonic value (e.g. cognitive absorption, perceived enjoyment, and playfulness), social value (e.g. subjective norm and social influence), and monetary value (e.g. price value) (Agarwal & Karahanna, 2000; Davis et al., 1989; Lowry, Gaskin, Twyman, Hammer, & Roberts, 2013; Venkatesh, Thong, & Xu, 2012). Perceived value has roots in behavioural decision theory and social psychology, and it can be defined as the users' justification for the experience of using the IS/IT in their daily life, regardless of whether this is for work or personal purposes (Okada, 2005). Moreover, the users' perceived value of an IS/IT is a cognitive trade-off between the perceived benefits and sacrifice of accepting the technology (Kim et al., 2017; Shin, 2017). The perceived benefits consist of increased job effectiveness, individual productivity and task innovation, and decreased effort devoted to task completion (Urbach & Müller, 2012). On the other hand, perceived sacrifices consist of the monetary cost (e.g. price value), privacy risk, and difficulties in use (e.g. complexity) that would hinder the users' acceptance (Moore & Benbasat, 1991; Venkatesh et al., 2012).

Perceived value can be defined as the users' cognitive overall assessment of using the IoT (Kim, Chan, & Gupta, 2007; Okada, 2005; Zeithaml, 1988). (Shin, 2017) studied the value of IoT from the utilitarian and hedonic points of view, suggesting that the perceived value positively influenced the quality of overall experience of IoT use. Taking into account that the IoT is delivered in the form of a service, the quality of experience critically determines the success of IoT implementation (Shin, 2017). The perceived value of IoT increased the users' continuance intention of smart devices that interact with public services (El-Haddadeh, Weerakkody, Osmani, Thakker, & Kapoor, 2018). The study of (Kim et al., 2017) viewed perceived value as an evaluation regarding the benefits and sacrifices, positively influencing the user's intention of accepting smart home services. (Jayashankar, Nilakanta, Johnston, Gill, & Burres, 2018) suggested that perceived value positively affected the adoption intention of smart agriculture technology. Existing studies have examined perceived value as antecedents of IoT acceptance and use because perceived value, especially the instrumental value, was viewed as closely related to the perceived usefulness in TAM (El-Haddadeh et al., 2018). Given that this study regards perceived value as a construct reflecting the perceived importance and overall evaluation of using the IoT in people's daily life, it proposes to examine the perceived value as an outcome of IoT use.

H3: Using the IoT is positively correlated with users' perceived value.

Following the above, this study devotes to examine the influence of the perceived characteristics of innovations on technology adoption. Drawing upon TAM and IDT, this study incorporates six determinants, namely, perceived usefulness, perceived ease of use, compatibility, result demonstrability, visibility and trialability, and tests their effects on the users' intention toward IoT adoption. Additionally, the diffusion of technology can be viewed as a process from technology creation, technology use, and the consequences of use (Delone & McLean, 2003; Karahanna, Straub, & Chervany, 1999). As such, this article explores the potential outcomes of IoT use as well. Based on the hypotheses presented above, the research framework was put forward as follows (Figure 1).

Figure 1. Research Framework



3. METHODOLOGY

3.1 Sampling and Data Collection

A questionnaire-based online survey was carried out to collect data for this study. An independent market research company organised the respondent recruitment, consisting of Internet users in the United States. Respondents were given the URL of the online survey and were asked to complete it. The authors did not have direct access to the respondents, which preserved their anonymity. 670 full questionnaires were initially received. Prior to the main survey, a pilot study was carried out with 10 participants. Based on the evaluation of this pilot study and the average completion time, collected questionnaires that had been completed in very short time were excluded from the dataset. This authors also removed questionnaires completed by selecting the same answer for most of the scaled measurement items, including the reversed one. By applying the above-stated criteria in the data screening process, 615 completed questionnaires were entered into the analysis. As the participants' profile (Table 1) illustrates, the participants of this research are the general population and have a reasonable distribution of demographic characteristics.

Table 1. Demographic Profile of Respondents

Demographic characteristic	Type	Frequency (n=615)	Percentage (%)
Gender	Male	266	43.3%
	Female	349	56.7%
Age	20-29	69	11.2%
	30-39	127	20.7%
	40-49	114	18.5%
	50-59	139	22.6%
	60 or over	166	27.0%
Current employment status	Full-time employed	258	42.0%
	Part-time employed	64	10.4%
	Out of work (looking for work)	26	4.2%
	Out of work (not looking for work)	6	1.0%
	Homemaker	77	12.5%
	Student	16	2.6%
	Retired	125	20.3%
	Unable to work	43	7.0%
Ethnicity	African American	65	10.6%
	Native American	6	1.0%
	USA White	452	73.5%
	Asian American	28	4.6%
	Hispanic American	37	6.0%
	Multiracial	8	1.3%
	Other White Background	15	2.4%
	Other	4	0.7%
Education attainment	Some high school or less	12	2.0%
	High school graduate or equivalent	118	19.2%
	Vocational/technical school	54	8.8%
	Some college, but no degree	157	25.5%
	College graduate	156	25.4%
	Some graduate school	22	3.6%
	Graduate degree	78	12.7%
	Professional degree	18	2.9%
Residence area	Urbanized area	256	41.6%
	Urban cluster	231	37.6%
	Rural area	128	20.8%
Household income	$0- $24,999	114	18.5%
	$25,000-$49,999	161	26.2%
	$50,000-$74,999	138	22.4%
	$75,000-$99,999	95	15.4%
	More than $100,000	107	17.4%

The questionnaire of this study consists of 34 measure items of the 9 constructs. This model included three variables adapted from TAM, four constructs selected from the perceived characteristics of innovation, and two potential outcomes of IoT use (Table 2). Measurement of the perceived usefulness, perceived ease of use, and behavioural intention of using the IoT were adapted from (Venkatesh, 2000). The measure items of perceived characteristics of innovation, i.e. compatibility, result demonstrability, visibility, and trialability, were adapted from the study of (Moore & Benbasat, 1991). Similar to the previous studies, items about well-being and perceived value were adapted from the studies of (El Hedhli, Chebat, & Sirgy, 2013) and (Okada, 2005) respectively.

Table 2. Measure Items of Constructs

Construct	Item	Label	Source
IoT Perceived Usefulness	Using the IoT improves my performance in my personal and work-related tasks.	IoT-PU1	(Venkatesh, 2000)
	Using the IoT in my personal and work-related tasks increases my productivity.	IoT-PU2	
	Using the IoT enhances my effectiveness in my personal and work-related tasks.	IoT-PU3	
	I find the IoT to be useful in my personal and work-related tasks.	IoT-PU4	
IoT Perceived Ease of Use	The IoT is clear and easy to understand.	IoT-PEOU1	(Venkatesh, 2000)
	Using the IoT does not require a lot of my effort.	IoT-PEOU2	
	I find the IoT to be easy to use.	IoT-PEOU3	
	I find it easy to get the IoT to do what I want it to do.	IoT-PEOU4	
Compatibility	The IoT will be compatible with all aspects of personal and work-related tasks.	CPT1	(Moore & Benbasat, 1991)
	The IoT will be completely compatible with my current situation.	CPT2	
	The IoT will fit well with the way I like to accomplish my tasks.	CPT3	
	The IoT will fit into my work style.	CPT4	
Result Demonstrability	I would have no difficulty telling others about the results of using IoT products.	RD1	(Moore & Benbasat, 1991)
	I believe I could communicate to others the consequences of using IoT products.	RD2	
	The results of using the IoT products are apparent to me.	RD3	
	I would have difficulty explaining why using the IoT products may or may not be beneficial.	RD4	
Visibility	I have seen what others do using IoT products.	VIS1	(Moore & Benbasat, 1991)
	In my community, one sees the others using IoT products.	VIS2	
	The use of IoT products is not very visible among my friends. *	VIS3	
	It is easy for me to observe others using IoT products.	VIS4	
Trialability	I've had a great deal of opportunity to try various IoT products.	TR1	(Moore & Benbasat, 1991)
	The IoT products were available to me to adequately test run various applications.	TR2	
	Before deciding whether to use any IoT products, I was able to properly try them out.	TR3	
	I was permitted to use IoT products on a trial basis long enough to see what it could do.	TR4	
IoT Behavioural Intention	I intend to use the IoT in the future.	IoT-BI1	(Venkatesh, 2000)
	I will try to use the IoT in my daily life.	IoT-BI2	
	I will plan to use the IoT frequently.	IoT-BI3	
IoT Well-being	The IoT will satisfy my overall needs.	IoT-WB1	(El Hedhli et al., 2013)
	The IoT will play a very important role in my social well-being.	IoT-WB2	
	The IoT will play a very important role in my social well-being.	IoT-WB3	
	The IoT will play an important role in enhancing the quality of my life in my community.	IoT-WB4	
IoT Perceived Value	Overall, what would be the value of the IoT for you personally?	IoT-PV1	(Okada, 2005)
	How well-off would you be with the IoT?	IoT-PV2	
	How happy would you be with the IoT?	IoT-PV3	

*Notes: * = Reverse item.*

3.2 Data Analysis

Multivariate analysis is widely used in addressing practical and theoretical research questions (Hair Jr, Black, Babin, & Anderson, 2014). A number of widely used multivariate techniques, such as multiple regression, factor analysis, multivariate analysis of variance, and discriminant analysis, expanded the explanatory ability of surveys (Hair Jr et al., 2014). However, these techniques have a common limitation in statistical efficiency in that they can examine only one relationship at a time and the relationship between only one independent variable and many dependent variables (Hair Jr et al., 2014). Structural equation modelling offers a number of advantages when compared with techniques such as those mentioned above in terms of (a) making it possible to examine a series of dependence relationships simultaneously; (b) it being particularly useful in testing dependence relationships of multiple equations; and (c) allowing for assessing measurement properties and testing theoretical relationships. This study employed structural equation modelling as the data analysis technique and followed the process suggested by (Hair Jr et al., 2014) and by (Gaskin, 2016). SPSS v.23 and SPSS Amos v.24 were used for the statistical analysis of the main hypotheses and moderation effects.

The following section presents the strategy of data analysis of this study. This research adopted three steps in the analysis, i.e. reliability and validity tests using confirmatory factor analysis, collinearity and common method bias tests, and hypotheses tests using structural equation modelling (Hair Jr et al., 2014). The next section presents details of the reliability and validity tests, and includes the results of confirmatory factor analysis and the correlations between the constructs of each model. Given that common method bias can be a potential issue for empirical studies using the same method to measure variables (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003; Richardson, Simmering, & Sturman, 2009), this study further estimates the common method variances.

3.3 Reliability and Validity Analysis

Reliability refers to the consistency between a variable and what it intended to measure, while validity describes the degree to which the measurements can correctly represent the concept of study (Hair Jr et al., 2014). Put differently, reliability describes how a variable is measured whereas validity concerns how well the concept is defined by the measurements. The construct reliability must be satisfied before assessing validity (Hair Jr et al., 2014). As such this research tested construct reliability, construct validity, and convergent validity by CFA. Three CFA models were established separately.

Table 3 reported the factor loadings of each item and construct reliability (C.R.), average variance extracted (AVE) and Cronbach's α of the variables. First of all, (Hair Jr et al., 2014) suggested that factor loadings greater than 0.3 are considered as having practical significance when the $N > 350$. To satisfy the criteria of construct reliability and validity, the standardized loading should be greater than 0.5 and ideally higher than 0.7 (Hair Jr et al., 2014). The measured variables should also satisfy the criteria of C.R. > 0.7, AVE > 0.5 and Cronbach's $\alpha > 0.7$. Given the above, some items were removed from the CFA model since they (a) fail to load with the expected factor, (b) have factor loading lower than 0.5, or (c) cause high cross-loadings. To this end, 6 items were removed from this study.

Table 3. Confirmatory Factor Analysis

	C.R.	AVE	Cronbach's α	Item	Loading
IoT Perceived Usefulness	0.958	0.884	0.958	IoT-PU1	Removed
				IoT-PU2	0.930
				IoT-PU3	0.955
				IoT-PU4	0.936
IoT Perceived Ease of Use	0.926	0.759	0.923	IoT-PEOU1	0.893
				IoT-PEOU2	0.733
				IoT-PEOU3	0.925
				IoT-PEOU4	0.918
Compatibility	0.959	0.853	0.958	CPT1	0.923
				CPT2	0.933
				CPT3	0.950
				CPT4	0.888
Result Demonstrability	0.914	0.781	0.914	RD1	0.847
				RD2	0.907
				RD3	0.896
				RD4	Removed
Visibility	0.894	0.808	0.894	VIS1	0.882
				VIS2	0.916
				VIS3	Removed
				VIS4	Removed
Trialability	0.937	0.832	0.937	TR1	Removed
				TR2	0.911
				TR3	0.916
				TR4	0.909
IoT Behavioural Intention	0.942	0.890	0.942	IoT-BI1	0.940
				IoT-BI2	0.947
				IoT-BI3	Removed
IoT Well-Being	0.962	0.863	0.961	IoT-WB1	0.915
				IoT-WB2	0.929
				IoT-WB3	0.946
				IoT-WB4	0.926
IoT Perceived Value	0.938	0.835	0.938	IoT-PV1	0.934
				IoT-PV2	0.880
				IoT-PV3	0.927

Notes: Method: M.L.; Model fit: $\chi 2(314) = 952.391$, CMIN/DF = 3.033, GFI = 0.902, CFI= 0.972, RMSEA= 0.058.

Convergent validity tests were carried out based on the CFA model, as presented in Table 4. Figures in the diagonal of each table represent the square root of the AVE and those below the diagonal represent the correlations between the constructs. The square root of the AVE is greater than the correlations between the constructs, suggesting that there was no convergent validity issue with the three research models (Hair Jr et al., 2014). Given the above, this study successfully established the reliability and validity of the constructs.

Table 4. Convergent Validity Test

	IoT-PU	IoT-PEOU	CPT	RD	VIS	TR	IoT-BI	IoT-WB	IoT-PV
IoT-PU	0.940								
IoT-PEOU	0.833	0.871							
CPT	0.855	0.754	0.924						
RD	0.751	0.787	0.786	0.884					
VIS	0.656	0.630	0.695	0.745	0.899				
TR	0.596	0.591	0.654	0.695	0.836	0.912			
IoT-BI	0.910	0.831	0.858	0.742	0.686	0.609	0.944		
IoT-WB	0.825	0.750	0.914	0.768	0.726	0.689	0.849	0.929	
IoT-PV	0.794	0.742	0.888	0.784	0.718	0.693	0.824	0.908	0.914

3.4 Collinearity and Common Method Bias Tests

Collinearity is a predictor-predictor phenomenon that occurs in multiple regression models. It exists when two or more predictors measure the same underlying construct (Kock, 2015). A full collinearity test should be conducted by calculating the variance inflation factor (VIF) based on multiple regression analysis (Kock, 2015; Kock & Lynn, 2012). In the context of co-variance-based SEM, VIF lower than 5 is the recommended threshold (Kline, 1998; Kock & Lynn, 2012) while VIF lower than or equal to 3.3 indicates that the research model is free of collinearity issues (Kock, 2015). Regression analysis of each dependent variable was run separately according to the composites of their predictors. Results showed that the VIFs ranged from 2.674 to 4.707. All of the VIFs were lower than the recommended threshold of 5, indicating that collinearity is not an issue in this study.

Common method bias (CMB), or common method variance, refers to the spurious variance that is attributed to the measurement method rather than to the constructs themselves (Podsakoff et al., 2003). CMB can be viewed as a "systematic error variance" shared among the variables being measured with a common scaling approach or from a single data source (Fuller, Simmering, Atinc, Atinc, & Babin, 2016; Richardson et al., 2009). A great deal of evidence indicates that CMB can (a) influence construct validity and reliability, (b) inflate or deflate the correlations between latent constructs, and (c) bias the true relationships between substantial variables (Fuller et al., 2016; MacKenzie & Podsakoff, 2012; Williams & Anderson, 1994). However, on the other hand, researchers have also suggested that the common method variance at a typical level of multiple-item measures is not a threat to the validity of research findings (Fuller et al., 2016).

This research adopted the common latent variable technique, or the marker variable approach, to estimate the size of method variance. This technique was applied to the three CFA models and included three steps (a) partialling out an unrelated variable as a surrogate/marker variable for common method variances, (b) loading all of the items on both their theoretical constructs and the marker variable that has its own measure items, and (c) constraining the parameters between research items and the marker variables to be equal (Lindell & Whitney, 2001; Podsakoff et al., 2003; Podsakoff & Organ, 1986). The marker variable in the case of this study is Job Satisfaction, which is theoretically unrelated to all of the constructs. Job Satisfaction was measured in the same approach with other constructs, i.e. the 7-point Likert scale, and included three items adapted from (Brayfield & Rothe, 1951), i.e. "I feel fairly satisfied with my present job", "most days I am enthusiastic about my work" and "I find real enjoyment in my work". The parameters between research items and Job Satisfaction represented the amounts of method variance in this study, i.e. 33.0%. These results suggest that the common method variances of each research model did not account for the majority of the variances. Therefore, this study is free of CMB issues.

Taking into account the above, this research adopted a full collinearity test and an estimation of the CMV using the marker variable approach. Statistical results indicated that collinearity is not problematic in this study and the research findings are not affected by CMB.

4. RESULTS AND FINDINGS

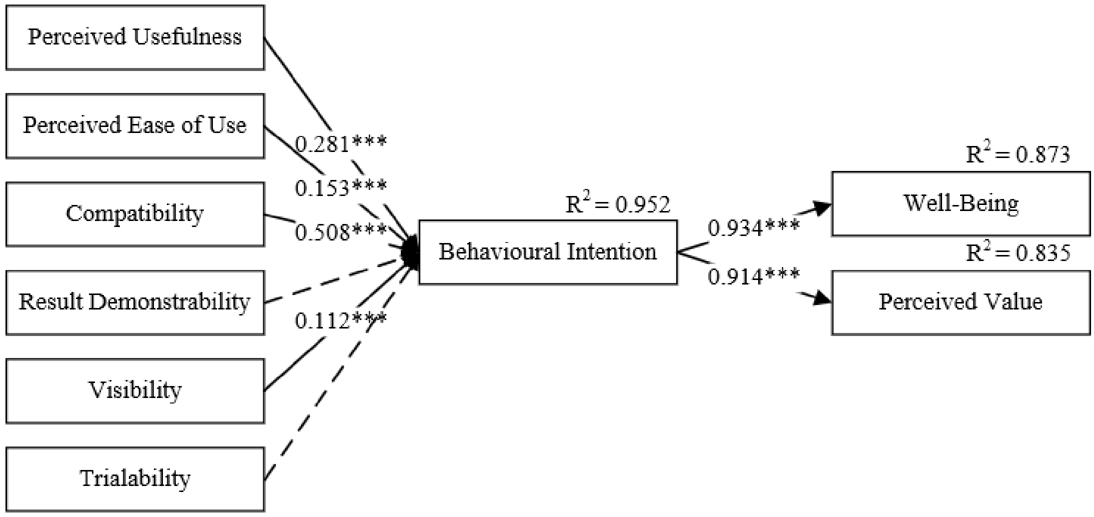
Structural equation modelling (SEM) was employed to test the hypotheses about the main effects. First of all, three SEM models were successfully established, by which the model fit criteria, i.e. $2 < CMIN/DF < 5$, $CFI > 0.9$, $RMSEA < 0.08$ (Hair Jr et al., 2014; Hooper, Coughlan, & Mullen, 2008), were satisfied. The R^2, direct effects, indirect effects, and total effects also suggested that the three SEM models explained a sufficient amount of variance.

Statistical results indicated an adequate level of fitness of the structural equation model of this study, i.e., CMIN/DF = 4.094, CFI= 0.955, RMSEA= 0.071. According to the model fit criteria suggested by (Hair Jr et al., 2014; Hooper et al., 2008), i.e., $2<CMIN/DF<5$, $CFI>0.9$, $RMSEA<0.08$, the research model of this study was successfully established. Table 5 and Figure 2 present the statistical results of the path analysis. Six out of the eight hypotheses were accepted, i.e., H1a, H1b, H1c, H1e, H2 and H3. Specifically, among the six perceived characteristics of the IoT, Perceived Usefulness (coef. = 0.281; $p<0.001$), Perceived Ease of Use (coef. = 0.153; $p<0.001$), Compatibility (coef. = 0.508; $p<0.001$), and Visibility (coef. = 0.112; $p<0.01$) showed significant and positive effects on the Behavioural Intention of IoT use. Also, Well-Being (coef. = 0.934; $p<0.001$) and Perceived Value (coef. = 0.914; $p<0.001$) were found to be significantly related to Behavioural Intention.

Table 6 presents the R^2 and the direct effects, indirect effects, and total effects of the three dependent variables, indicating a satisfied practical significance of the research model. The R^2 of IoT Behavioural Intention is 0.952, which suggests that the six perceived characteristics sufficiently and largely explained the variances in the users' intention of accepting the IoT (Moore, 2010). This research model also explained a substantial amount of the effects on Well-Being (R^2=0.873) and

Perceived Value (R^2=0.835). Notably, Compatibility is the most powerful IoT characteristic and it represented the largest amount of the direct effect on Behavioural Intention (Table 6).

Figure 2. Path Significances and Estimates



*Notes: Significant at p: ns = > .05; * = < .05; ** = < .01; *** = < .001*

Table 5. Structural Equation Model and Hypotheses Test (H3.1-H3.3)

Hypotheses	**Path**			**Coef. (t-test)**
H1a	IoT Perceived Usefulness	→	IoT Behavioural Intention	0.281 (6.801***)
H1b	IoT Perceived Ease of Use	→	IoT Behavioural Intention	0.153 (4.458***)
H1c	Compatibility	→	IoT Behavioural Intention	0.508 (13.261***)
H1d	Result Demonstrability	→	IoT Behavioural Intention	-0.022 (-0.632ns)
H1e	Visibility	→	IoT Behavioural Intention	0.112 (3.056**)
H1f	Trialability	→	IoT Behavioural Intention	0.029 (0.916ns)
H2	IoT Behavioural Intention	→	IoT Well-Being	0.934 (30.906***)
H3	IoT Behavioural Intention	→	IoT Perceived Value	0.914 (30.267***)

Notes: Method: M.L.; Model fit: χ2 (327) = 1338.596 , CMIN/DF = 4.094, CFI= 0.955, RMSEA= 0.071
*Significant at p: ns = > .05; * = < .05; ** = < .01; *** = < .001.*

Table 6. R^2 and Effect Size

Dependent Variable	**R^2**	**Independent Variable**	**Direct Effect**	**Indirect Effect**	**Total Effect**
IoT Behavioural Intention	0.952	IoT Perceived Usefulness	0.281		0.281
		IoT Perceived Ease of Use	0.153		0.153
		Compatibility	0.508		0.508
		Result Demonstrability	-0.022		-0.022
		Visibility	0.112		0.112
		Trialability	0.029		0.029
IoT Well-Being	0.873	IoT Perceived Usefulness		0.262	0.262
		IoT Perceived Ease of Use		0.143	0.143
		Compatibility		0.475	0.475
		Result Demonstrability		-0.021	-0.021
		Visibility		0.105	0.105
		Trialability		0.028	0.028

		IoT Behavioural Intention	0.934		0.934
IoT Perceived Value	0.835	IoT Perceived Usefulness		0.256	0.256
		IoT Perceived Ease of Use		0.139	0.139
		Compatibility		0.464	0.464
		Result Demonstrability		-0.020	-0.020
		Visibility		0.103	0.103
		Trialability		0.027	0.027
		IoT Behavioural Intention	0.914		0.914

5. DISCUSSION

The findings indicated that the six determinants adapted from TAM and IDT sufficiently explained variances in users' behavioural intention of using the IoT. Specifically, perceived usefulness, perceived ease of use, compatibility and visibility had significant positive effects on the users' intention of using the IoT, whereas demonstrability and trialability did not show significant influence on IoT adoption decisions.

First of all, perceived usefulness is one of the leading factors determining user acceptance and adoption (Abu-Khadra & Ziadat, 2012). The positive effect of perceived usefulness on behavioural intention suggested that the instrumental value and the functionality of the IoT that can enhance the users' performance in completing certain tasks is critical to the potential users. Perceived ease of use had a significant but relatively small influence on the users' adoption decisions on IoT. This finding is in correspondence with the results of (Gao & Bai, 2014; Liew et al., 2017; Mital et al., 2017; Park et al., 2017) but in contrast with (Bao et al., 2014).

Compatibility is the most influential factor driving IoT adoption, indicating that the consistency between the IoT services and their current situation is one of the users' concerns (Moore & Benbasat, 1991). These results confirmed the findings of (Bao et al., 2014; Hubert et al., 2018; Karahoca et al., 2017; Park et al., 2017; Shin, 2017; Wang et al., 2018). Then, this result confirmed the finding of (Karahoca et al., 2017). Visibility significantly affects one's intention to adopt the IoT as well, supporting the viewpoint that the smart devices which are apparent to the users' sense of sight will encourage them to adopt (Agarwal & Prasad, 1997; Chuah et al., 2016). On the other hand, statistical results suggested that result demonstrability and trialability do not have any influence on the users' intention. One potential explanation is that the uncertainty of using IoT products is not the users' main concern, thus the tangibility of the results of use and opportunities to try the products before adoption would not affect their intention (Dutta & Omolayole, 2016).

The strong positive effects of intention of IoT use on the expected outcomes suggest that the potential users believe that the IoT has value in their daily life and they expect the IoT to benefit their well-being. These findings confirmed that using the IoT is believed to be of importance to the users' daily life (El-Haddadeh et al., 2018; Shin, 2017) and would benefit them in terms of enhancing their well-being (Marikyan et al., 2018; Martínez-Caro et al., 2018; Mital et al., 2017; Papa et al., 2018; Spaceti, 2017).

6. CONCLUSION, IMPLICATION, AND LIMITATIONS

This study considered IoT adoption as a critical part of the innovation diffusion process, and it thus examined the effects of characteristics of innovation on the users' adoption decisions. The successful establishment of the research model indicated that the perceived characteristics of innovation sufficiently explained variances in users' behavioural intention of adopting the IoT. Statistical results suggested that the compatibility between IoT applications and the users' current situations and target tasks is the main concern. Also, the instrumental value and the visibility of IoT devices play important roles in encouraging the users to adopt the IoT. This study contributed to providing further insights into IoT literature by elaborating the effects of the attributes of innovation on the users' intention of adoption and examining the acceptance and adoption of the IoT platform instead of one specific service. This research also contributes to the existing body of knowledge about technology acceptance, adoption and use. Specifically, this research provided valuable insights into the MIS theories in terms of extending the commonly used intention-based causal chain by incorporating the users' motivations of technology acceptance and potential outcomes of technology use.

This research is not without limitations. This study statistically tested the research models using data collected from consumers in the U.S. Although these models performed well in elaborating the factors influencing user acceptance and adoption of the IoT, the compatibility of research model should be examined in other contexts, such as users in societies with different cultural backgrounds. This provides a potential research avenue in examining and validating the research framework in other settings. Besides, a number of factors that potentially influence user acceptance and use of the IoT should be explored and examined in the future. For instance, in addition to the typical characteristics of innovation investigated in this study, the unique characteristic of the IoT such as the ubiquitous distribution of sensors and the users' concerns about privacy invasion could be investigated in the future. Also, psychological factors concerning IoT use and the personal attributes of IoT users should be investigated.

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