Asia Pacific Journal of Information Systems
Vol. 28 No. 4 (December 2018), 320-349

ISSN 2288-5404 (Print) / ISSN 2288-6818 (Online)
https://doi.org/10.14329/apjis.2018.28.4.320

An Integrated Framework for Modeling the Influential Factors Affecting the Use of Voice-Enabled IoT Devices: A Case Study of Amazon Echo

Temidayo Oluwapelumi Shofolahan[a], Juyoung Kang[b,*]

[a] *Independent scholar, Markam, Ontario*
[b] *Professor, School of Business, Ajou University, Korea*

A B S T R A C T

Purpose: The application of IoT is finding continuous acceptance in our daily lives, particularly, smart speakers are making life easier and convenient for consumers. This research aims to develop and test an integrated model of factors influencing consumer's adoption of voice-enabled IoT devices.
Design/methodology/approach: Based on the VAM, an integrated voice-enabled IoT device adoption model is proposed. Gender differences on five constructs relating with perceived value (perceived usefulness, perceived enjoyment, perceived security risk, perceived technicality and perceived cost) was also examined through PLS-MGA technique. The usage experience of consumers was also controlled in the integrated VAM.
Findings: Result shows that Perceived-Usefulness, Perceived-Enjoyment and Perceived-Cost have a strong effect on Perceived-Value. However, Perceived-Technicality and Perceived-Security-Risk are non-influential and have no significant effect on PV. Additionally, Perceived-Value and Social-Influence plays a significant role in predicting adoption intention. Gender differences also exist in consumers perception of usefulness, enjoyment and cost. In comparison to the basic value-based adoption model, the integrated model provides more insight on consumers adoption of voice-enabled IoT devices.
Originality/value: Using an integrated model, this study is one of the first scholarly attempt at modelling the influential factors for adopting smart speakers i.e., voice-enabled IoT devices, with implications for improved adoption.

Keywords: Amazon Echo, Voice-enabled IoT Devices, Consumer Perception, Adoption Intention, Integrated Value-based Adoption Model

Ⅰ. Introduction

The launch of the internet in 1963 provided the

*Corresponding Author. E-mail: jykang@ajou.ac.kr Tel: 82312192910

world with a technology that helped to connect several computers for the transmission of information, since then, the adoption of internet for various purposes have grown tremendously with more than 4.15 billion internet users as at early June, 2018 (Miniwatts Marketing Group, 2017). The invention and adoption of the internet has led to the invention of better, faster and efficient technologies relying on internet technology, one of which is the Internet-of-Things. Also known as IoT, the internet is used for the connectivity of physical objects using special sensors embedded in them. Through this, users of IoT devices can initiate real-time contact with all other supported IoT devices from a central control point like a smartphone or smart speaker to make use of IoT services (Kowatsch and Maass, 2012).

According to Columbus (2017), the IoT market is expected to reach $276 Billion by 2020, the main reason for this rapid growth of IoT is the rapid adoption of the IoT services by governments, businesses and individuals. Reports estimate that there will be 75.44 billion IoT connected devices in the world by 2025 (Statista, 2018). The Smart Home market, which is a huge segment of the IoT industry is growing at a lightening pace, this is due to the increasing sales of smart home products which is promoted and encouraged by rising internet penetration and reduction of price of processors which are the embedded cores of IoT devices. Within the space of 7 years, the American household smart home adoption increased from less than 0.5% in 2010 to 7% by 2017 and more homes will continuously adopt smart technologies which will further increase the rate to 10% by 2025 (Transparency Market Research, 2017).

The Smart home market received a significant boost in 2014 with the invention of Amazon smart home voice assistant, called the Amazon Echo, the first smart speaker/voice-enabled IoT device purposely designed for the traditional home. The success of the smart home product spurred the interest of other companies and as at 2017, the Google Home, Nugu and Apple HomePod have been developed as formidable competitors of the Amazon Echo. As the IoT market continues to grow, a clear and comprehensive understanding of voice-enabled IoT device adoption is therefore essential to understand consumer's sentiments, and essential factors influencing their behavioral intention. Despite the phenomenal growth, IoT is still in its infancy or non-existent in most countries. Although, it is acclaimed that IoT applications could enhance quality of life and work efficiency, the adoption could be better, according to Accenture, 87% of electronic consumers still haven't heard about IoT (Accenture, 2014).

While there has been a gradual increase in the trend of using IoT applications due to its potentials, only a few studies (Hsu and Judy, 2016) have investigated how individuals use IoT applications and the sentiments surrounding its adoption. Previous research has mainly focused on the technical branch of IoT e.g., (Qian and Wang, 2012; Xu et al., 2014), none has considered end user's perspective of IoT applications like voice-enabled IoT devices. As with any technological innovation, IoT also has its advantages and weak points that may influence adoption, many users and consumers are still skeptical with the mental effort required to use IoT devices, privacy issues and other problems like cost of IoT devices and the information security related with using a technology that has access to a broad range of user information. In the aspect of cost, individual consumers are also hindered by not the actual purchase cost of using IoT devices but the service subscriptions and continuous use costs like buying of other IoT devices to achieve a comfortable user experience, thereby increasing consumer's spending (Kim, 2018).

Studies have found that while cost is not often a significant issue in commercial adoption of technology due to its ability to reduce a firm's operation cost, it is an important and significant issue for individual consumers in deciding to adopt smart technologies (Kim and Shin, 2015).

For the study of technology adoption and usage, researchers often use the TAM, VAM and UTAUT (Venkatesh et al., 2003) models. The Technology Adoption Model (TAM), an extension of the theory of reasoned action and an information systems theory that models how users come to accept and use a technology (Davis et al., 1989). Despite the wide use of TAM, it is better for studying the adoption of traditional technologies and inappropriate in the explanation of user's adoption of new technology such as IoT. The difference between traditional technology users and new technology users is the former works in organizations where the cost of using the technology is supported by the organization while the latter uses technology for individual reasons and therefore bear the cost individually (Kim et al., 2017).

The Value-based Adoption Model (VAM) is used for the study of factors that drive technology adoption from the consumer perception of value to be obtained. It is efficient in examining consumer behavior through the value maximization perspective, it takes into consideration a couple of variables representing the sacrifice-based construct and the benefit-based construct and thus present adoption of technology as a comparison of benefits and sacrifices involved in using a technology. To find out the attributes that influence consumer adoption of IoT products, this research uses the value-based adoption model (VAM). The VAM model uses a principle that helps to understands a consumer decision making process, the costs and benefits associated with buying an IoT product like the smart speaker is compared to capture the concept of the product's value. Consumers always want the best value for their money and every penny they pay for goods needs to be thought of as a worthwhile venture i.e., more benefits, less cost.

Previous studies have investigated Internet of Things adoption through the lens of IoT services as a whole using the VAM (Hsu and Judy, 2018), and from the perspective of commercial application of IoT technologies such as electronic toll collection using the TAM (Gao and Bai, 2014), this research differs from previous studies by studying IoT adoption with a focus on smart home products (smart speakers/voice-enabled IoT devices) with an integrated framework that consists of social context and value maximization factors. It investigates the impact of perceived benefits and perceived sacrifices on perceived value and adoption intention, and, the effect of social context on consumer adoption of voice-enabled IoT devices. An additional investigation of the gender differences in the factors affecting individual decision to adopt IoT is also carried out. The findings will help IoT products/services companies to serve customers better by understanding the factors behind consumer's sentiments & adoption of smart speakers and to set up effective marketing strategies to improve adoption.

The research is structured as follows. First, a simple introduction stating how the research is organized is made. Second, the details of some literatures used in this study are stated in the next section. Third, the hypotheses are proposed to explain the relationships of all the constructs used in this study. Fourth, the research methodology explaining how primary data will be collected, structured and analyzed is presented. Fifth, through the testing of the measurement and structural models, the primary data collected is analyzed and the result of the study is explained. Sixth, in terms of the results, an explanation and discussion of the reasons behind the findings obtained is performed. Finally, a conclusion to summarize this study is done.

Ⅱ. Literature Review

2.1. Internet of Things

This research focuses on voice-enabled IoT devices and one of the common application of IoT is in the home to implement a phenomenon known as the "smart home", IoT devices comprise the major part of the concept of home automation, where the refrigerator, coffee maker, television, lighting, heating, air conditioning and any home device can be commanded to perform functions as required by the user. IoT technology can be used to relay real time information which is applied in environment services to give weather update in case of wildfire or earthquake, in the transportation sector, it's use ranges from electronic toll collection, to traffic management and self-driving cars, in the health sector, it is used for glucose level and blood pressure monitoring through sensors embedded in the physical body (Dimitrov, 2016), in the home, it is also implemented in smart technologies like smart refrigerator, smart television, and smart kitchen gadgets (Pătru et al., 2016).

According to Abdmeziem et al. (2016), the IoT architecture consists of the perception layer which perceives the physical properties of things around us that are part of the IoT, based on several sensing technologies (e.g., RFID, WSN, GPS, NFC, etc.), the network layer which is responsible for processing the received data from the perception Layer and the application layer which uses the processed data by the previous Layer and constitutes the front end of the whole IoT architecture through which the IoT potential will be exploited. This is the layer through which the value of voice-enabled IoT devices can be perceived, as indicated in the purpose of this research.

Regarding the main reason of the study, which is to understand the adoption of voice-enabled IoT devices by consumers from the social context and value perspective, several previous studies related to the general adoption of technologies is reviewed.

2.2. Technology Adoption

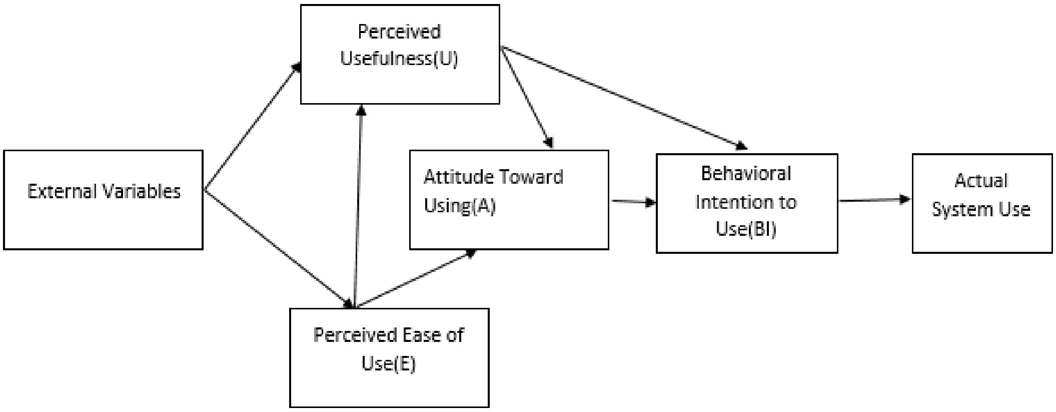
Consumer's adoption of technology has continuously attracted the attention of many researchers. Several studies has investigated the adoption of technologies like the Mobile internet (Roostika, 2012), Mobile payment (Abrahão et al., 2016), Enterprise 2.0 (Lin et al., 2010), Mobile commerce (Chong, 2013; Ko et al., 2009), Cloud computing (Kwon and Seo, 2013), Internet of Things (Al-Momani et al., 2016) and others. <Table 1> summarized the literature review of technology adoption, which as we can infer is often explored by using the Technology Adoption Model (TAM), the Unified Theory of Acceptance and use of Technology Model (UTAUT) and the Value-based Adoption Model (VAM).

TAM, also known as the technology adoption model is an adaptation of the theory of reasoned action and a theoretical model introduced by (Davis et al., 1989), the framework was created to predict, explain and improve the user acceptance of computer systems based on user's behavioral intentions and to also, understand why people adopt and oppose computer technology. Through Davis' research, the determinants of computer acceptance were identified as the user's attitude towards using computer system in addition to the perceived usefulness of the computer

<Table 1> Previous Research on Adoption Intention

Research method	Independent variable(s)	Mediating Variable	Dependent variable	Description	Reference
(VAM) Internet survey	Benefit & Sacrifice	Perceived value	Adoption Intention	To examine the adoption of Mobile Internet from the value perspective	Kim et al. (2007)
(TAM) Survey	Perceived usefulness, Perceived ease of use, Trust, Social Influence, Perceived enjoyment, Perceived behavioral control	-	Behavioral intention	To identify factors determining the consumer acceptance of IOT technology	Gao and Bai (2014)
(VAM) Internet Survey	Perceived usefulness, Perceived enjoyment, Perceived fee, Perceived privacy risk	Perceived value	Adoption Intention	Exploring factors affecting the adoption of IoT services	Hsu and Judy (2016)
(TRA & TAM) Laboratory & Survey	Attitude toward adoption Social influence		Adoption Intention	Investigating the role of social influence on consumers adoption of technology	Kulviwat et al. (2009)
(VAM) Survey	Perceived benefits Perceived costs	Perceived value	Adoption intention	Understanding the Intention to adopt enterprise 2.0	Lin et al. (2010)
(UTAUT) Survey	Performance expectancy Effort expectancy Social influence Personal innovativeness Trust Perceived enjoyment Facilitating conditions Perceived value		m-commerce adoption	Identifying the predictors of m-commerce adoption	Chong (2013)
(VAM) Survey	Perceived benefit Perceived sacrifice	Perceived value	Adoption intentions	Analyzing perceived value relations to mobile internet adoption	Roostika (2012)
(VAM) Korean companies	Perceived benefit Perceived sacrifice	Perceived value	Adoption intentions	Understanding company user's SaaS adoption	Kwon and Seo (2013)
(VAM) Internet survey	Perceived benefit Perceived sacrifice	Perceived value	Adoption intentions	Adoption intention of mobile shopping of fashion products	Ko et al. (2009)
(UTAUT) Survey	Performance expectation Effort expectation Social influence Perceived risk Perceived cost		Behavioral intention	Adoption of mobile payment service	Abrahão et al. (2016)
(S-D logic) Survey	Superior functionality Aesthetic appeal Ease of use Presence	Perceived value co-creation	Continuance intention Word-of-mouth intentions	Value co-creation with IOT in retail industry	Balaji and Roy (2017)

system. According to (Sharma and Mishra, 2014), the limitations of TAM is in the fast pace at which new information technology is invented in the IT environment, an example is some decades ago 2G was a luxury, this was quickly replaced by 3G and at 2018, the development of 5G is almost a completed task. Quantum computing was also a futuristic technology until 2017, today the development of com-



<Figure 1> Fully Developed Technology Acceptance Model

puters based on quantum technology is a realistic occurrence with IBM and Google reporting a successful endeavor in the field (IBM, 2018).

The proposed formula and model for the TAM-related study was:

Behavioral Intention (BI) = Attitude (A) + Perceived Usefulness (U)

The model has been used in the several studies like (Gao and Bai, 2014) to understand the adoption of IoT technologies. While the TAM is effective in understanding user's behavioral intention, its effectiveness has been questioned in studies trying to understand user's behavioral intention toward information technology from the value perspective for personal uses. Hence, the TAM would not be efficient in this research.

UTAUT, also known as the Unified Theory of Acceptance and Use of Technology is a theoretical model developed to improve on the weakness of the TAM. It was a model developed by (Venkatesh et al., 2012) to study the acceptance and use of technology in a consumer context, and it effectiveness was justified because it accounted for 70% of the variance in behavioral intention to use a technology compared to previous studies. The UTAUT uses four key constructs of performance expectancy, effort expectancy, social influence, and facilitating conditions to measure the behavioral intention to use a technology. While the UTAUT is effective in understanding user's behavioral intentions and takes the social context of the consumer into consideration, this study's aim is to understand user's behavioral intention toward information technology from both the social and value perspective. Hence, it would serve us less in this research.

2.3. Adoption of Voice-Enabled IoT Devices from the Value Perspective, The Value -Based Adoption Model

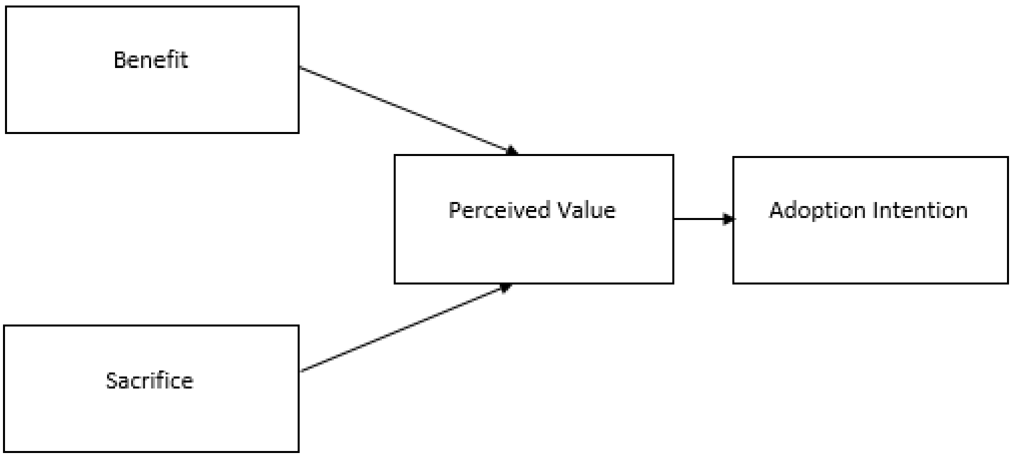
The value-based adoption model is developed from the perspective of a cost-benefit paradigm, to explain people's decision-making strategies based on a number of perceptual factors with the aim of making a rewarding decision (Davis, 1989). The value-based adoption model, also known as VAM is the revamping of the concept of perceived value which according to (Zeithaml, 1988) is “the consumer's overall assessment of the utility of a product (or service) based on perceptions of what is received and what is given". It was stressed further that, consumers think of perceived value in the context of low price, little effort, benefit received, and satisfaction obtained from the use of a product. According to the economic theory of utility, consumers are able to select from a broad range of goods and services and natural intuition makes them opt for goods and services with the best benefits. In other words, the value obtained from using a good or service is related to its marginal utility and consumers will rank their preferences accordingly.

This study looks to extend the scope of the model by adding other latent factors that affects present day consumers of technology like social influence and the conceptual moderating variables of gender that affects the adoption IoT devices while also controlling all variables in the conceptual framework for spuriousness with the usage experience variable of consumers. Speaking in the context of value maximization, the VAM can be used to predict IoT adoption. The model has been demonstrated in research involving adoption of mobile internet (Kim et al., 2007) and cloud computing (Kwon and Seo, 2013). The two papers proposed that perceived value is affected by perceived benefits and perceived sacrifices.

Ⅲ. Hypotheses and Research Model

3.1. The Hypotheses of the Research Model

The value-based adoption model is used by capturing a small number of factors that account for most of the variance in adoption intention to make it easier to predict IoT adoption (Kim et al., 2007). The basic figure of the value-based adoption model is further explained and illustrated below. It states that consumer intention to adopt IoT is determined by perceived value and social influence. Furthermore, perceived value is affected by, and mediates the impact of benefit (i.e., perceived usefulness and perceived enjoyment) and sacrifice (i.e., perceived security risk, perceived technicality and perceived cost). The categorical construct of gender is adopted as a moderator in the conceptual model.



<Figure 2> The Basic Concept of Value-Based Adoption Model (VAM)

3.1.1. Perceived Benefit

The constructs of 'Usefulness' and 'Enjoyment' of IoT devices were adapted for perceived benefits. Usefulness is defined as the ability of an IoT device be used for a practical purpose and/or in several ways. Perceived usefulness is an extrinsic motivator and the degree to which a person believes that using an IS would enhance the effectiveness of performing a process (Davis, 1989), improve the performance of the process, improve the speed and quality of performing the process and obtain information fundamental to performing the current process or future activities. IoT devices can help users get traffic information and avoid congested transportation infrastructures at crunch hours, obtain the air index quality to prepare for outdoor activities and avoid disease/infection, and make it possible to perform several tasks simultaneously through connection to other IoT devices. IoT technologies are expected to attain an improved rate of adoption provided they contribute significantly to the consumer's daily activities (Gao and Bai, 2014). The VAM has proven that perceived usefulness has a positive effect on perceived value (Hsu and Judy, 2016; Kang and Moon, 2013; Kwon and Seo, 2013), it is therefore expected that a similar outcome will be obtained in this research. Therefore, it is hypothesized that,

H1: Perceived usefulness will have a positive effect on the perceived value of IoT devices.

Perceived enjoyment is an intrinsic motivator defined as the extent to which a person believes that using IoT devices would provide pleasure, fun, enjoyment and fulfilment. Consumers who experience pleasure from using technology are more intrinsically motivated to adopt them (Gao and Bai, 2014), and research has proven that perceived enjoyment will have a positive effect on perceived value of using mobile internet services (Kim et al., 2007). Furthermore, in a study of mobile shopping for fashion products, (Ko et al., 2009) showed that asides perceived usefulness, perceived enjoyment has a strong positive effect on the perceived value of an IS. It is therefore expected that a similar outcome will be obtained in this research by extending these results to the context of IoT devices adoption. Therefore, it is hypothesized that,

H2: Perceived enjoyment will have a positive effect on the perceived value of IoT devices.

3.1.2. Perceived Sacrifice

Perceived sacrifice can imply both monetary efforts i.e. the price paid for a product and nonmonetary efforts i.e. time, energy and mental effort invested in using a product (Zeithaml, 1988). The constructs of 'Security', 'Technicality' and 'Cost' were adopted to represent nonmonetary and monetary efforts of perceived sacrifice. Perceived security risk is defined as the user's belief regarding the general security of the IoT architecture. This can be with respect to the security uncertainty due to lack of awareness and potential loss of confidential and personal information due to the use of IoT devices (Hsu and Judy, 2016). The issue of security is an ever evolving phenomenon in information systems, even more in IoT, hackers will often behave opportunistically and intrude into systems when afforded the chance, it has being discovered by top technology corporations that IoT devices is the weapon of choice in distributed denial of service (DDOS) attacks due to the poor security awareness of IoT device users (Akamai, 2017; Barcena and Wueest, 2015; Symantec, 2016). Security of sensitive data and existing regulation on data privacy and protection makes the provision of customize services that meet customer needs difficult to achieve (Kwon and Seo, 2013). In the study of important security factors of IoT, 30 IoT professionals have expressed perceived privacy risk, legislation, data security, and transparency of information as a potential influencer of adoption of IoT services (Kowatsch and Maass, 2012). Therefore, it is hypothesized that,

H3: Perceived security risk will have a negative effect on the perceived value of IoT devices.

Using insights provided by (Kwon and Seo, 2013) with regards to the technicality of technology, perceived technicality is a factor of the user's perception of an IoT system reliability, connectivity, efficiency and ease of use. Perceived technicality in this research is concerned with ease of usage perspective held by consumers, the mental and physical effort like the information technology literacy & knowledge required to use voice-enabled IoT devices and the time taken to get IoT devices working. Studies show that perceived technicality of a technology is an important factor and consumers will use a technology if they believe it does not require great effort to use (Davis, 1989; Gao and Bai, 2014). IoT is a technology that can be used for different purposes by different users, the ability to customize IoT devices based on user needs is also important in the study of technicality. An example is the smart home configuration of IoT users which is different based on household. Kim et al. (2007)'s research shows that the technicality surrounding the use of M-internet is a negative influence on the perceived value of M-Internet. IoT devices being a new product that is yet to be widely adopted may likely be viewed as too complex to use, as the characteristics of voice-enabled IoT devices have not been fully studied in previous information systems research, the perception of technicality needs to be considered as it may impact consumer's perceived value and intention to adopt IoT devices. Therefore, it is hypothesized that,

H4: Perceived technicality will have a negative effect on the perceived value of IoT devices.

Cost is an important factor in an individual's decision making process (Al-Momani et al., 2016). Perceived fee is the amount of economic outlay that must be sacrificed to obtain a technology (Hsu and Judy, 2016). In this study, the word cost is preferred because fees may be perceived by consumers as simply the purchase cost of voice-enabled IoT devices, but the perceived cost used in this study includes the cost of obtaining, maintaining and implementing other IoT devices in a smart home i.e., purchase and use cost e.g., constant internet connectivity cost, constant energy cost for powering IoT devices, cost of subscribing to related IoT services like Amazon Shopify etc. Perceived cost is also defined as the extent to which a consumer believes that adopting and using IoT devices will cost money. The cheaper the cost, the higher the perceived value and the more likely it is for a product or service to be adopted (Grewal et al., 1998). In the case of Amazon Echo, consumers would likely consider the fact that implementing it in a smart home requires other IoT enabled devices to enjoy a flawless smart home setting, making investment in additional electronics a necessity, and thereby shaping the consumer's perception of the cost. Perceived price is a sub-construct of perceived sacrifice and influences perceived value and adoption intention negatively (Dodds et al., 1991). Furthermore, perceived cost and pricing structure of a product has a significant impact on consumer's perception of value and adoption intention (Kim et al., 2007; Venkatesh et al., 2012). Therefore, it is hypothesized that,

H5: Perceived cost will have a negative effect on the perceived value of IoT devices.

3.1.3. Perceived Value and Adoption Intention

From the concept of the VAM, perceived value is a mediator of the relationship between perceived benefits, perceived sacrifices and adoption intention (Lin et al., 2010). Perceived value is the consumer's overall perception of IoT services based on consideration of benefits and sacrifices, it reflects the economic theory of utility in which customers try to gain most from a service at an unrestrained economical cost, consumers do this by comparing benefits with sacrifices and is therefore an indicator of adoption intention (Kwon and Seo, 2013). In addition, previous studies have proved a strong relationship between perceived value and adoption intention (Kuo et al., 2009; Wang and Wang, 2010). It is therefore expected that if the perceived value of IoT devices is high, it would impact consumer's decision to adopt them, and it is hypothesized that,

H6: Perceived value have a positive effect on intention to adopt IoT devices.

3.1.4. Social Influence and Adoption Intention

By extending the scope of the VAM, social influence is included to examine how social context impact consumer's decision to adopt IoT devices. Introduced in the UTAUT model, Social influence is the extent to which an individual perceives that important others like colleagues and family believe he or she should use an IS (Venkatesh et al., 2003). It is a constituent of subjective norms, social factors and social status of a consumer. Several studies have shown social influence to impact the adoption of technology and services by consumers (Abrahão et al., 2016; Chong, 2013; Venkatesh et al., 2012). Humans are social beings and our emotions are often affected in light of how we are portrayed. In the study of high tech innovations, (Kulviwat et al., 2009) stated that social influence positively affects the adoption intention of consumers especially when the use of the product can be noticed by others. As IoT devices falls into this category of innovations, it gives more incentives to investigate how social influence impact IoT device adoption. It is therefore hypothesized that,

H7: Social influence will have a positive effect on intention to adopt IoT devices

3.1.5. Control Variable

Previous IT experience is an important determinant of behavior (Bagozzi, 1981). Through the examination of all the previous studies cited till this extent in this study, the use of control variables in the value-based adoption model has not been observed. Consumers familiarity with IoT devices differs, while some are ardent users, others are apathetic, collecting responses from a broad range of people and making generalizations would therefore reduce the adequacy of this research. To prevent this, it is found pertinent to include a control variable of Amazon Echo usage experience (across 3 levels) of consumers as portrayed by (Chiu et al., 2005) to eliminate issues arising from common method variance and experimental error. This will further assure the reliability & validity of the conceptual model and help to make the appropriate inferences of adoption intention through the application of dummy coding.

3.1.6. Moderating Variables

Gender:

Based on grounded-theory studies, (Ahuja and Thatcher, 2005) assessed the influence of gender on information technology innovation & adoption and proved that the adoption of technology varies by gender. Based on the UTAUT model, a study of the effect of gender on the intention to use mobile chat technology has shown influence of gender differences on specific latent variables with perceived enjoyment showing a stronger effect for women than men (Nysveen et al., 2005). A study of social network users by (Thelwall, 2008) also showed different uses of technology based on gender with males using technology for a different purpose compared to females. (Goswami and Dutta, 2015) examined several studies spanning the period of 16 years (2000-2015) and illustrated how the use of technology differs on gender basis. Other studies like (Chiu et al., 2005; Venkatesh and Morris, 2000; Venkatesh et al., 2000) has also shown differences in decision to adopt technology on the basis of gender. Therefore, based on previous theories and to explore how this phenomenon applies in the value-based adoption model, it is hypothesized that:

H8a: Perceived usefulness of IoT devices will have a stronger positive effect on perceived value for males than females

H8b: Perceived enjoyment of IoT devices will have a stronger positive effect on perceived value for females than males

H8c: Perceived security risk of IoT devices will have a stronger negative effect on perceived value for males than females

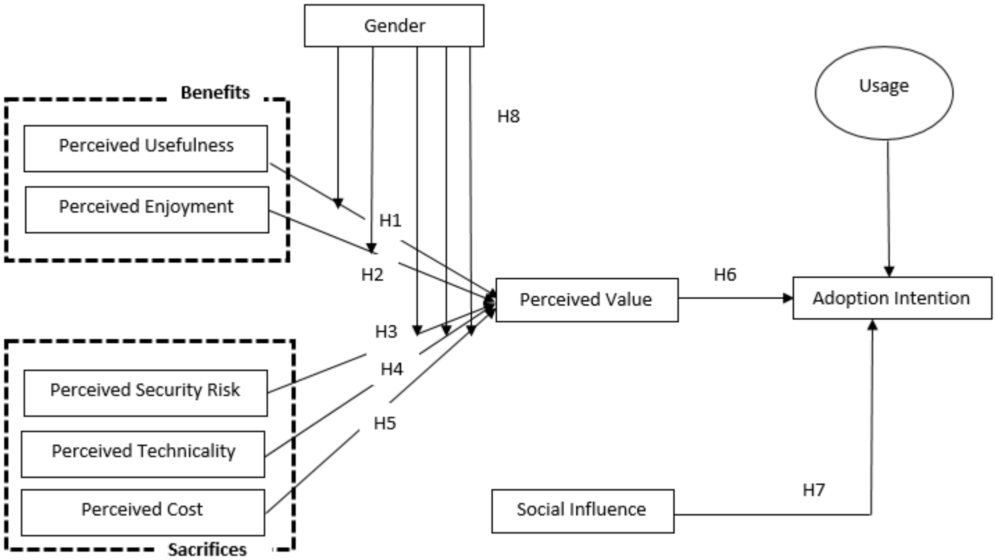
H8d: Perceived technicality of IoT devices will have a stronger negative effect on perceived value for females than males

H8e: Perceived cost of IoT devices will have a stronger negative effect on perceived value for females than male

The moderating test will be performed with Partial Least Squares-Multi Group Analysis (PLS-MGA) technique provided with the SmartPLS 3.2.7 application and as illustrated by (Sarstedt et al., 2011). The multigroup analysis will enable both male and female groups to be tested to see if there are significant differences in their parameter estimates (e.g., outer weights, outer loadings and path coefficients). The male group selected under Group A will be compared against female group selected under Group B and an outcome will be obtained based on bootstrapping results from the sub-groups of gender (male and female). To visualize this, the method explained by (Aiken et al., 1991) is used through SPSS to plot the 2-way interaction effects as illustrated in <Figure 5>.

3.2. Research Model

Perceived usefulness and perceived satisfaction are operationalized as the perceived benefits of using voice-enabled IoT devices. Perceived security, perceived technicality and perceived cost are operationalized as the perceived sacrifice of using voice-enabled IoT devices. Social influence is operationalized as the social context surrounding the use of voice-enabled IoT devices. Gender is operationalized as the moderator of all relationships with perceived value in the model. The usage experience of consumers is operationalized as a control of the adoption intention variable. Along with the hypotheses and the



<Figure 3> The Conceptual Research Model

framework mentioned in the theoretical background, the research model is presented as <Figure 3> above.

Ⅳ. Research Methodology

The hypotheses and casual linkage between variables of the research model were discussed in the previous section, this section focuses on explaining the measurement instruments and the primary data collection method after clarifying the definition of constructs. The definition of each construct is summarized in <Table 2>.

4.1. Measurements Development and Data Collection

The cross-sectional data used in this research was contracted to a private online survey company that provide responses collected from specifically targeted consumers in the USA, the data was collected over the course of a week. The research questionnaire consists of two sections. The first section is designed to collect the respondent's demographic information like age, gender, Amazon Echo usage experience, and familiarity with various Amazon Echo features. The latter section is developed from questions adopted from previous related studies that were sometimes modified to fit the present research and to measure each research construct. To refine the data collection process, disqualification and skip logic was applied to prevent respondents who do not possess the voice-enabled IoT device, Amazon Echo, from participating in the survey. <Appendix A> illustrates the final questionnaire as presented to respondents. Each item used in this research was measured with a 5-point likert scale raging from "strongly disagree" to "strongly agree".

4.2. Pilot Study

To test for ambiguity, the initial questionnaire

<Table 2> Construct Definitions and References

Construct	Definition	References
Perceived usefulness	Percieved usefulness is the degree to which a person believes that using Amazon Echo would enhance his or her duties.	(Davis, 1989)
Perceived enjoyment	Perceived enjoyment is the extent to which a person believes that using Amazon Echo would provide pleasure, fun, enjoyment and fulfilment	(Kim et al., 2007)
Perceived security risk	Perceived security risk is the degree of the user's belief regarding the general security of Amazon Echo.	(Hsu and Judy, 2016)
Perceived technicality	Perceived technicality is the degree to which a person believes that using Amazon Echo would be free of effort.	(Davis, 1989)
Perceived cost	Perceived cost is the extent to which a consumer believes that adopting and using Amazon Echo will cost money.	(Kim et al., 2007)
Perceived value	Perceived value is the consumer's overall perception of Amazon Echo based on consideration of benefits and sacrifices.	(Kim et al., 2007)
Social influence	Social influence is the extent to which an individual perceives that important others like colleagues and family believe he or she should use Amazon Echo.	(Venkatesh et al., 2003)
Adoption intention	Adoption intention is the decision of a consumer to use Amazon Echo based on a number of decisive factors.	(Kim et al., 2007; Venkatesh et al., 2012)

was posted on a social media forum frequented by Americans and a pilot study consisting of 18 responses were collected. Every construct used had significant reliability and validity. Some items related to adoption intention and perceived usefulness in the initial questionnaire had factor loadings of less than 0.7, although the construct of these items had high reliability and validity, a decision was made to delete the items. Opinion of respondents was also used to improve the sentence structure of some items to remove confusion. The final questionnaire is in <Appendix A>.

4.3. Main Survey

Among the 320 questionnaires sent out to consumers, 197 responses were received, 38 were dropped due to disqualification (non-users of Amazon Echo) and therefore, incomplete responses. The final survey used in this research was therefore collected from 159 respondents who are conversant users and owners of Amazon Echo. The demographic detail is illustrated in <Table 3>.

Out of the six Amazon Echo functions selected to be inquired from consumers, using the smart speaker for listening to music and seeking of general information emerged as the two most frequently utilized functions, this is followed by smart home control, shopping, listening to a book and finally, scheduling in a descending order of frequency.

Ⅴ. Data Analysis and Results

5.1. Measurement Model

A total of 10 constructs were used in this research. Using SPSS and mostly SmartPLS3, the reliability, validity, and structural model tests of the research constructs is conducted.

<Table 3> Demographics of Respondents (N = 159)

Measure	Items		Subjects	
			Frequency	Percentage (%)
Gender	Male		57	35.85
	Female		102	64.15
Age	Under 19		3	1.89
	20-29		36	22.64
	30-39		23	14.47
	Over 40		97	61.00
Usage Experience	Less than 1 year		90	56.60
	1-3 years		57	35.85
	Over 3 years		12	7.55
Experience of using Amazon Echo for Various Purposes	Listening to Music	*Never*	22	13.84
		Often	53	33.33
		Frequently	84	52.83
	Smart home Control	*Never*	92	57.86
		Often	37	23.27
		Frequently	30	18.87
	Listening to a book or article	*Never*	86	54.09
		Often	49	30.82
		Frequently	24	15.09
	Schedule arrangement	*Never*	87	54.72
		Often	55	34.59
		Frequently	17	10.70
	Shopping	*Never*	95	59.75
		Often	40	25.16
		Frequently	24	15.09
	Seeking of general information	*Never*	29	18.24
		Often	65	40.88
		Frequently	65	40.88
Total			159	100

5.1.1. Reliability

Regarded as the extent to which several items measure a single construct, reliability test helps to ensure quality of measurements carried out in a research. It is a quality of measurement method that ensures same data would be obtained for several specific observations of the same phenomenon. As illustrated by <Table 4>, Firstly, the indicator reliability which is indicated by the outer loading values range within 0.752 and 0.971. Secondly, the internal consistency reliability is also examined, the Cronbach's alpha

<Table 4> Reliability and Convergent Validity of Constructs

Item	Measure	Outer Loadings	Composite Reliability	Cronbach's alpha (α)	AVE	Mean	SD
PU1	Using Amazon Echo improves my work/life performance.	0.871	0.925	0.892	0.756	3.28	1.01
PU2	Using Amazon Echo enhances my work effectiveness and lifestyle.	0.895					
PU3	Using Amazon Echo enables me to accomplish my task more quickly.	0.863					
PU4	Using Amazon Echo help me get information useful for my work and personal life.	0.849					
PE1	While using Amazon Echo, I experience pleasure.	0.932	0.949	0.920	0.861	3.49	0.99
PE2	The process of using Amazon Echo is enjoyable.	0.915					
PE3	I obtain fun from using Amazon Echo.	0.937					
PSR1	There is a security risk involved in using Amazon Echo.	0.852	0.937	0.910	0.787	3.55	0.97
PSR2	There is too much security uncertainty associated with using Amazon Echo.	0.888					
PSR3	My decision to use Amazon Echo exposes me to security risks.	0.905					
PSR4	Using Amazon Echo would lead to a loss of privacy.	0.902					
PT1	It is not easy to make use of amazon echo.	0.909	0.937	0.900	0.832	2.44	1.08
PT2	It is not easy to learn how to utilize Amazon echo.	0.901					
PT3	I find my interaction with amazon echo quite unclear and not understandable.	0.927					
PC1	The cost I must bear for the use of Amazon Echo is too high.	0.903	0.931	0.889	0.817	2.75	1.03
PC2	The cost I must bear for the use of Amazon Echo is not reasonable.	0.892					
PC3	I am not pleased with the cost I must bear for the use of Amazon Echo.	0.918					
PV1	Compared to the fee I need to pay; the use of Amazon echo offers value for money.	0.907	0.958	0.941	0.850	3.37	1.00
PV2	Taking all the pros and cons into consideration, the use of Amazon echo is beneficial to me.	0.921					
PV3	Compared to the time and effort I need to put in, the use of Amazon echo is beneficial to me.	0.914					
PV4	Overall, the use of Amazon Echo gives me good value.	0.945					

<Table 4> Reliability and Convergent Validity of Constructs (Cont.)

Item	Measure	Outer Loadings	Composite Reliability	Cronbach's alpha (α)	AVE	Mean	SD
SI1	People who are important to me would recommend using Amazon echo.	0.857	0.924	0.889	0.754	3.38	0.99
SI2	People who are important to me would find using Amazon echo beneficial.	0.931					
SI3	People who are important to me would find using Amazon echo a good idea.	0.922					
SI4	It is expected that people like me use amazon echo.	0.752					
AI1	I intend to keep using Amazon Echo in the future.	0.971	0.967	0.948	0.907	3.47	1.12
AI2	I intend to continue using Amazon Echo.	0.968					
AI3	I intend to recommend the use of Amazon Echo to my friends in the future.	0.917					

Note: PU: perceived usefulness; PE: perceived enjoyment; PSR: perceived security risk; PT: perceived technicality; PC: perceived cost; PV: perceived value; SI: social influence; AI: adoption intention

and composite reliability values for all the research constructs are higher than 0.7. Considering these results, the constructs reliability is confirmed.

5.1.2. Convergent and Discriminant Validity

Convergent validity was used to ensure that the research constructs that are meant to be related are in fact, related. This is assessed with the Average Variance Extracted values for all eight constructs, and they are all greater than 0.5 (<Table 4>), thereby confirming the convergent validity of this research. Discriminant validity tests that research construct that are meant to be unrelated are in fact, not related. We assess this with the Fornell-Larcker Criterion (<Table 5>), the square root of AVE for each of the eight latent variables is found to be greater than the correlations among the eight latent variables. Therefore, discriminant validity is significantly confirmed.

5.1.3. Multicollinearity

Multicollinearity assessment is used to check for the potential of collinearity problem in the seven exogenous latent variables- Perceived Usefulness, Perceived Enjoyment, Perceived Security Risk, Perceived Technicality, Perceived Cost, Perceived Value and Social Influence. The rule of thumb which states that the VIF values of the exogenous variables (<Table 6>) must be less than 5 applies in the case of this research. Therefore, multicollinearity is confirmed not to be a problem in this research.

5.2. Structural Model

A hypothesis test is conducted using SmartPLS 3.2.7 to examine the effect of the antecedents (PU, PE, PSR, PT, PC) on PV and SI on AI. Further, the effect of PV on AI was also investigated. In addition to the explanation in section 3.1.5, it was discovered from the data that 56.6% of the respondents are users with less than one-year experience, with users having 1-3 years or more than 3 years usage experience having less representation in the sample data, the decision to control respondent's experience of using Amazon Echo in the conceptual model is

<Table 5> Discriminant Validity of Constructs (Fornell-Larcker Criterion)

Constructs	AI	PC	PE	PSR	PT	PU	PV	SI	Usage
AI	0.952								
PC	-0.544	0.904							
PE	0.708	-0.265	0.928						
PSR	-0.466	0.561	-0.249	0.887					
PT	-0.517	0.605	-0.393	0.345	0.912				
PU	0.618	-0.205	0.731	-0.177	-0.309	0.869			
PV	0.834	-0.476	0.687	-0.375	-0.439	0.658	0.922		
SI	0.717	-0.355	0.725	-0.312	-0.403	0.601	0.662	0.868	
Usage	0.162	-0.109	0.150	0.175	-0.094	0.128	0.102	0.158	1.000

<Table 6> Collinearity Statistics (Inner VIF Values)

Constructs	AI	PC	PE	PSR	PT	PU	PV	SI	Usage
AI							1.780	1.807	1.026
PV		2.031	2.326	1.484	1.741	2.148			

therefore further validated. Using Bootstrapping analysis of 5000 samples as recommended by (Hair et al., 2016), the statistical significance of the research constructs is tested, and the coefficient of determination R^2 and the path coefficients are estimated. Based on this process, <Figure 4> illustrates the outcome and path coefficients of all 8 main constructs and the results of the hypothesis is illustrated in <Table 7>.

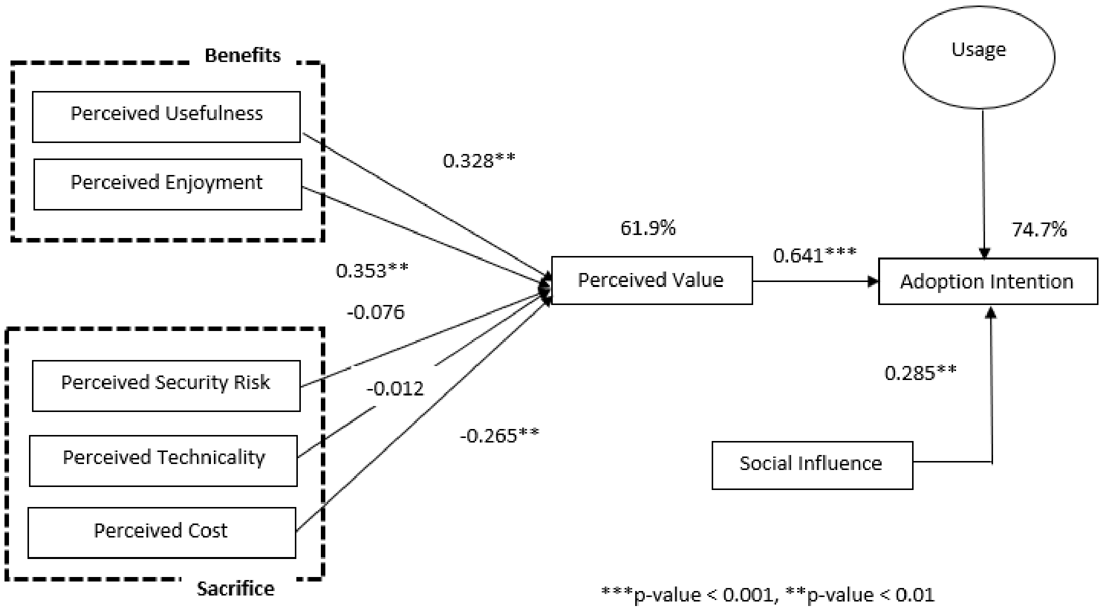
For the benefits section of the integrated value-based adoption model, the relationship between the two benefit variables and perceived value is positively significant. The path coefficient of perceived usefulness → perceived value & perceived enjoyment → perceived value is (0.328) and (0.353) respectively. Thus, H1 and H2 is both supported at p-value < 0.01.

For the sacrifice section of the integrated value-based adoption model, the path coefficient of perceived cost → perceived value is negatively significant (-0.265), thus, H5 is supported at p-value < 0.01, However, the path coefficients of perceived security risk → perceived value and perceived technicality → perceived value is (-0.076) and (-0.012) respectively with p-value > 0.1. Thus, H3 and H4 is rejected.

The relationship between perceived value and adoption intention has a path coefficient of (0.641) and supports the hypothesis that user's perceived value of voice-enabled IoT devices like Amazon Echo positively influence adoption intention keeping in control the usage experience of the consumer. Therefore, H6 is supported at p-value < 0.001.

The relationship between social influence and adoption intention has a path coefficient of (0.285), supporting the hypothesis that the immediate physical and social setting in which people live positively influence adoption intention of voice-enabled IoT devices. Therefore, H7 is supported at p-value < 0.01.

The moderating effect on PU, PE, PSR, PT & PC, using the gender categorical variable is also examined using PLS-MGA approach. Hypothesis H8a is supported with the effect of perceived usefulness on

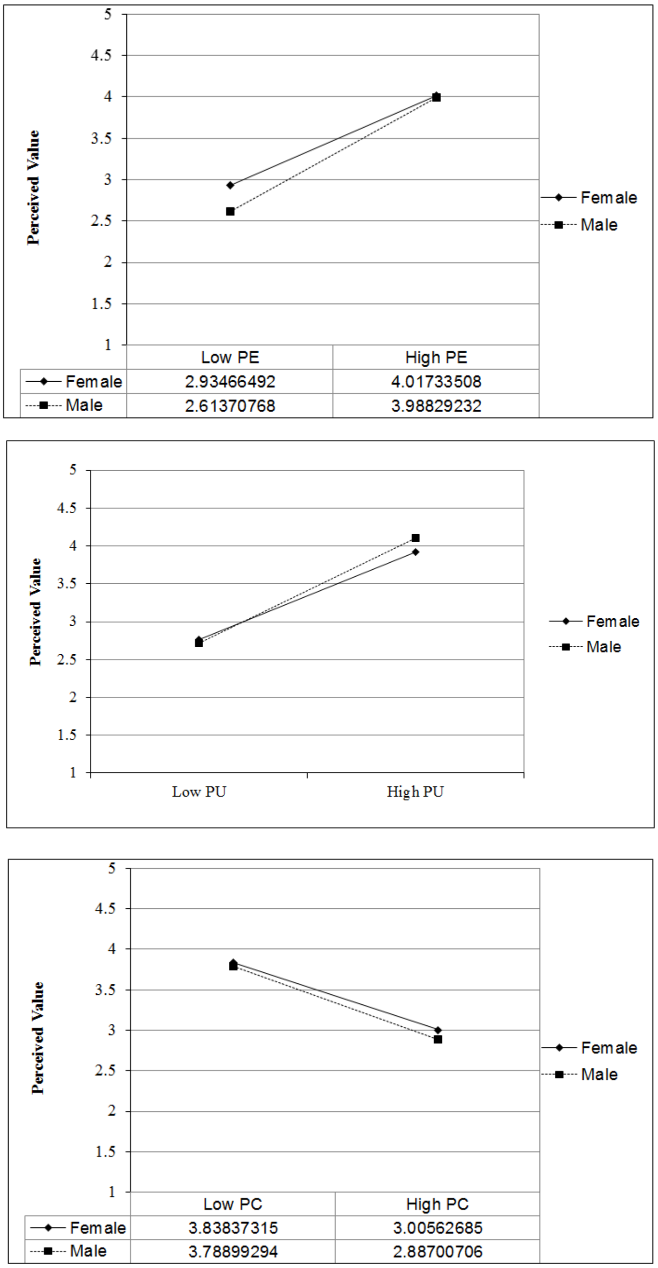


<Figure 4> Result of Research Model

<Table 7> Hypothesis Results

Path	Path coefficient	T-value	Hypothesis
(H1) PU → PV	0.328	3.104	Supported
(H2) PE → PV	0.353	3.201	Supported
(H3) PSR → PV	*-0.076*	*1.073*	*Not supported*
(H4) PT → PV	*-0.012*	*0.128*	*Not supported*
(H5) PC → PV	-0.265	2.950	Supported
(H6) PV → AI	0.641	8.514	Supported
(H7) SI → AI	0.285	3.187	Supported
(H8a) PU*Gender → PV	0.671	5.818	Supported
(H8b) PE*Gender → PV	0.523	4.784	Supported
*(H8c) PSR*Gender → PV*	*-0.001*	*0.009*	*Not supported*
*(H8d) PT*Gender → PV*	*-0.009*	*0.080*	*Not supported*
(H8e) PC*Gender → PV	-0.317	2.700	Supported

perceived value more positively significant for males than females at p-value < 0.001. H8b is supported with the perceived enjoyment of Amazon Echo having a stronger positive effect on perceived value for females than males at p-value < 0.001, Hypothesis H8e is also supported with the perceived cost of voice-enabled IoT devices showing a stronger negative effect on perceived value for females than males at $p < 0.01$, H8c and H8d is not supported across both groups.



<Figure 5> Moderating Effect Plots

The R^2 output indicates that perceived usefulness(PU), perceived enjoyment (PE), perceived security risk(PSR), perceived technicality(PT) and perceived cost(PC) accounts for 61.9% of the variance in voice-enabled IoT device's perceived value, and 74.7% of the variance in adoption intention (AI) of IoT device is determined by perceived value (PV) and social influence (SI) of Amazon Echo's users, keeping in control the usage experience, this value reduces to 73.4% without the control variable, although a slight effect but it indicates the importance of implementing a control variable in the model. This significance is also supported by (Becker, 2005) who recommends the proper manner and procedure of operationalizing control variables in research. The extension of the VAM by including the social influence (SI) construct in the integrated model also improves the prediction of voice-enabled IoT device adoption, this is evident from analysis since the percentage of observed variance in the intention to use IoT devices drops by 4.3% to 70.4% without considering the social context of consumers. The integrated model indicates more effectiveness and improvement in the modelling of IoT adoption significantly building on the progress made in previous research works using simplified VAM (Hsu and Judy, 2016) or even extended TAM model (Gao and Bai, 2014).

Ⅵ. Discussion And Conclusion

6.1. Discussion

This study explored consumers adoption intention towards voice-enabled IoT devices with the aid of an integrated model developed by extending the individual value-based adoption model (VAM). The perceived benefits of voice-enabled IoT devices were found to have more impact on perceived value of voice-enabled IoT devices than the perceived sacrifices. In addition, perceived value was found to significantly account for consumers adoption of voice-enabled IoT devices. Perceived value was also found to be completely dependent on the perceived benefit and sacrifice constructs exempting perceived security risk and perceived technicality of using voice-enabled IoT devices. This was because the perceived security risk and perceived technicality constructs of the perceived sacrifice section was discovered to be an insignificant factor considered by consumers in their decision to adopt voice-enabled IoT devices. As part of the ways of improving on previous research and addressing the gap in the literature, the social context of consumers and the moderating variable of gender was introduced as part of an integrated model and determined to be an important, significant and influential factor that can predict consumers adoption intention towards voice-enabled IoT devices. Elaboration of this findings in relation to their theoretical & practical implications as well as some future research suggestions is made in the subsequent section.

6.2. Theoretical Implications

This research has helped to improve the comprehension of factors impacting voice-enabled IoT device adoption from the consumer perspective with the proposed model (R^2 = 0.747). Perceived benefits (perceived usefulness and perceived enjoyment) seems to have a greater impact than perceived sacrifices (perceived security risk, perceived technicality and perceived cost), implying that perceived benefits play a very essential role in determining the perceived value of IoT devices. A regression of perceived value with benefit and sacrifice constructs separately shows a R^2 value of 0.525 and 0.280 respectively. In this situation where consumers are provided with factors and information to make the best decision, this is consistent with the rational choice theory (Becker, 2013), which means individuals will actively maximize their advantage in any situation. Since voice-enable IoT devices provide consumers with useful and enjoyable features, consumers are attracted by the benefits provided.

Benefits like perceived usefulness and perceived enjoyment continues to appear as an important determinant of IoT device adoption. Perceived usefulness was found to be the second most important determinant of perceived value (β = 0.328, p-value < 0.01) and perceived enjoyment was the most important determinant of perceived value (β = 0.353, p-value < 0.01) proving perceived enjoyment as the most important reason for consumer's adoption of voice-enabled IoT devices. This result distinguishes this study from related prior studies like (Han et al., 2013; Hsu and Judy, 2016; Kim et al., 2007) who suggested that perceived usefulness is the most important determinant of intention to use, through perceived value. A possible reason for this is explained by the research performed by (Bruner II and Kumar, 2005) who suggested while consumers requires an IS to be useful, when technological devices do not require lots of mental efforts to operate and can be used easily to perform various activities, consumers will obtain greater enjoyment from using them, this is proven further in this research because consumers of Amazon Echo do not find the IoT device technically complex to operate. Perceived usefulness and perceived enjoyment as utilitarian and hedonic components of technology respectively, can significantly influence perceived value of an IS. This means that as consumers continue to perceive various uses of IoT device in their daily life while also obtaining pleasure from using the device to perform tasks, adoption will continually increase.

Sacrifices like the perceived cost of using IoT devices was found to significantly impact the perceived value of IoT devices negatively (β = -0.265, p-value < 0.01), this is consistent with prior research done by (Han and Yang, 2010; Lin et al., 2012) who suggested that the perceived fee of using technology is the most powerful barrier to adoption and reduces the perceived value of an IS. Amazon Echo as an IoT device often require other IoT capable electronics and devices to perform tasks and investment in these additional electronics would make consumers quite reluctant to adopt IoT devices.

In previous researches by (Kwon and Seo, 2013; Lin et al., 2010), security related perceptions like privacy of consumers while using technology was found to significantly affect perceived value negatively, technical complexity was also found to negatively impact the perceived value of an IS, perceived security risk and perceived technicality was discovered to have a different perception by consumers in this research as they have no significant impact on perceived value, thereby maintaining consistency with the research of (Han et al., 2013). One possible explanation for this is an increase in awareness of consumers regarding how to safeguard their devices by changing the default password of devices after purchase, also, according to data provided by OECD, compared to previous years, the computer and internet literacy of an average person has increased tremendously with technology users finding it easy compared to latter years to use an IS (OECD, 2018). The gap in literature years serve as a second explanation, those researches were conducted at least 5 years ago when IS adoption was at its early stages and therefore still relatively new to consumers. In addition, a report released by three organizations investigating the consumer adoption of smart speakers in 2018 revealed that privacy and security concern do not serve as an hindrance to adoption (Voicebot.ai, 2018).

The foundation of the VAM in predicting adoption intention is the consumer's perceived value, and perceived value has a strong positive effect (β = 0.641, p-value < 0.001) on adoption intention.

Supporting (Kulviwat et al., 2009) findings, this study found that social influence positively influences adoption of technology. The integrated value-based adoption model shows the direct positive effect of social influence (β = 0.285, p-value < 0.01) on voice-enabled IoT device adoption and indicates that consumers are influenced by their social environment. (Venkatesh et al., 2003) suggested that older women with less experience of using a new technology tends to be more responsive to others opinion and therefore find social influence to be more crucial when deciding to adopt technology, this is very similar in this research as 64% of respondents are females, 57% have used IoT devices for less than a year and 61% is over the age of 40. It is therefore imperative that social influence factors should be considered in the process of improving voice-enabled IoT device adoption.

6.3. Practical Implications

For the voice-enabled IoT device industry, the following recommendations is provided. Investigated from the perspective of benefit, sacrifice and social context based on an integrated value-based adoption model, it is discovered in this research that Benefits (PU, PE), Sacrifice (PC), and Social context (SI) are the important influencers of perceived value and adoption intention, with sacrifice playing a lesser role due to the insignificance of perceived security risk and perceived technicality. Voice-enabled IoT device providers should strive to continually improve consumers perceived usefulness of IoT by integrating more functionalities which consumers can use for even more activities, therefore bringing additional benefits to consumers. Using the smart home as an example, the convenience of consumers can be improved through automation of more tasks by providing more IoT enabled devices that can be interconnected with each other. The perceived enjoyment of consumers should also not be overlooked as its found to be even more important than perceived usefulness, more work can be done to provide further hedonic benefits to consumers in various ways.

For an improved enjoyment of voice-enabled IoT devices, feature discoverability and product tips can serve as a benefit to existing users to get more value out of newly added features, thereby making the process of using the gadget even more enjoyable. This can also help users to better understand the product and enforce the spirit of product adoption, continuous use and probably, referrals. As consumers of voice-enabled IoT devices finds using the device an easy task, the addition of more functionalities should not be done at the expense of consumers enjoyment, as it has been found that, the more difficult it is to use a technology, the lesser consumer's perceived enjoyment becomes (Bruner II and Kumar, 2005).

The sacrifice-based construct of perceived cost has a yet negative effect on consumers perceived value of voice-enabled IoT devices, although much work has been done on competitive pricing and a continuous saturated market has further crashed the cost of voice-enabled IoT devices, more work needs to be done to improve the perceived cost of voice-enabled IoT devices. Based on data obtained from some respondents willing to share their annual financial income, majority of these respondents, have an annual household income greater than $50,000USD. It is believed this group of people may find the purchase cost of Amazon Echo reasonable, and their perception of cost might have been influenced by the use cost of IoT devices like the purchase of smart televisions, smart refrigerators and other gadgets which can be integrated with the IoT system. To solve this problem, it is recommended that IoT device providers like Amazon and Google form joint marketing campaigns with business organizations like Samsung and LG, who manufacture and provide smart electronics in order to promote their devices together and improve the cost perception of consumers through reduced pricing of the products, this collaboration may be capable of encouraging an increased adoption of the products.

The cost perception of users can be reduced because such collaboration can allow partnering companies to leverage their visibility to promote individual products, and by combining forces, each company spends less than they would otherwise on their own because the advertising cost is shared, and some percentage of this cost savings can be redirected towards product price reduction. This can also help consumers to engage the beneficial synergies the joint marketing relationship promises. Based on analysis, the current users of voice-enabled IoT devices find the security guards of IoT devices reasonable and using the device is assumed as a non-risky behavior, however, security is an ever-revolving concept in IoT, therefore, investment into the research and development of IoT architecture and security should be maintained and updated according to the recommended industry standards, policies and best practices (ENISA, 2017). Security can also become a systematic and collaborative decision making process involving not just government and industry but also, the retailers and end users (Blythe and Johnson, 2018). Perceived technicality does not have a negative effect on perceived value, although IoT is a new form of technology and consumer's first impression may be that it is a difficult technology that requires a lot of mental effort, this study shows that the current interface of voice-enabled IoT devices i.e. Amazon Echo, is well-designed, and presented to consumers in a manner that facilitates an easy operation. The current interface should be maintained in improving consumers intention to adopt voice-enabled IoT devices.

With the wide adoption of digital media, the social environment of consumers is currently being capitalized on as a customer acquisition tool. The careful use of social media influencers who are focused on technology and whose reputation and image complements a product can be further utilized by companies in reaching more prospective users through endorsement campaigns. Famous social media influencers serving as a reference-group can convince potential voice-enabled IoT device adopters and reduce uncertainty towards adopting them.

Also, the gender of voice-enabled IoT device consumers should be given attention to improve consumer targeting strategies, this was found to affect the association between consumers perceived usefulness, enjoyment, cost and the perception of voice-enabled IoT device value. It is also recommended to include specific control variables in the VAM while studying IoT device adoption, as usage length of IoT consumers was found to improve the co-efficient of determination R^2 by 1.3% from 73.4% to 74.7% in this study due to the inclusion of control variables.

6.4. Limitations and Future Research

First, a vast majority of the respondents from which data was obtained in this research have used voice-enabled IoT devices for less than a year, there is a probability that their perceptions may change with more usage experience, further studies may investigate this in the future with a longitudinal approach as the adoption of voice-enabled IoT device increases. Second, there is a clear distinction between privately used IoT devices and commercially used ones, therefore, the findings made in this research may not apply elsewhere when the conditions are changed as all the respondents in this research are private users that operates Amazon echo in a smart home setting. Third, the sample size could be improved upon, the decision to use a sample size of 159 online survey respondents was because finding qualified respondents was difficult despite much time and financial investment in getting respondents.

Further research can improve the sample size considerably, use data collected from several countries or use panel data to make extensive future findings. Also, primary and secondary data can be used to make a similar research that is based on the commercial adoption of IoT. Fourth, the respondents in this research are residents of USA, generalizing these results to other countries should be done with caution. This research allows voice-enabled IoT device manufacturers and developers to understand the general factors that dictates consumer's adoption of IoT. The research outcome is assumed to be fair and unbiased because the weakness of the researches done previously is handled here with the inclusion of social context, moderating and control variables in the VAM, while there may be some limitations in the research, having outcomes consistent with prior studies and postulations enhances confidence in the results obtained.

<References>

[1] Abdmeziem, M. R., Tandjaoui, D., and Romdhani, I. (2016). Architecting the internet of things: state of the art. *Robots and Sensor Clouds* (pp. 55-75): Springer.

[2] Abrahão, R. de S., Moriguchi, S. N., and Andrade, D. F. (2016). Intention of adoption of mobile payment: An analysis in the light of the Unified Theory of Acceptance and Use of Technology (UTAUT). *RAI Revista de Administração e Inovação, 13*(3), 221-230.

[3] Accenture (2014). *The Internet of Things: The future of consumer Adoption*. Retrieved from https://www.accenture.com/t20150624T211456__w__/us-en/_acnmedia/Accenture/Conversion-Assets/DotCom/Documents/Global/PDF/Technology_9/Accenture-Internet-Things.pdf

[4] Ahuja, M. K., and Thatcher, J. B. (2005). Moving beyond intentions and toward the theory of trying: effects of work environment and gender on post-adoption information technology use. *MIS quarterly, 29*(3), 427-459.

[5] Aiken, L. S., West, S. G., and Reno, R. R. (1991). *Multiple regression: Testing and interpreting interactions*. Sage Publications.

[6] Akamai (2017). *Threat advisory: Internet of Things and the Rise of 300 Gbps DDoS Attacks*. Retrieved from https://www.akamai.com/us/en/multimedia/documents/social/q4-state-of-the-internet-security-spotlight-iot-rise-of-300-gbp-ddos-attacks.pdf

[7] Al-Momani, A. M., Mahmoud, M. A., and Sharifuddin, M. (2016). Modeling the adoption of internet of things services: A conceptual framework. *IJAR, 2*(5), 361-367.

[8] Bagozzi, R. P. (1981). Attitudes, intentions, and behavior: A test of some key hypotheses. *Journal of personality and social psychology, 41*(4), 607.

[9] Balaji, M., and Roy, S. K. (2017). Value co-creation with Internet of things technology in the retail industry. *Journal of Marketing Management, 33*(1-2), 7-31.

[10] Barcena, M. B., and Wueest, C. (2015). *Insecurity in the Internet of Things*. Retrieved from https://www.symantec.com/content/dam/symantec/docs/security-center/white-papers/insecurity-in-the-internet-of-things-15-en.pdf

[11] Becker, G. S. (2013). *The economic approach to human behavior*. University of Chicago press.

[12] Becker, T. E. (2005). Potential problems in the statistical control of variables in organizational

research: A qualitative analysis with recommendations. *Organizational Research Methods, 8*(3), 274-289.

[13] Blythe, J., and Johnson, S. (2018). *The Consumer Security Index for IoT: A protocol for developing an index to improve consumer decision making and to incentivize greater security provision in IoT devices*.

[14] Bruner II, G. C., and Kumar, A. (2005). Explaining consumer acceptance of handheld Internet devices. *Journal of Business Research, 58*(5), 553-558.

[15] Chiu, Y.-B., Lin, C.-P., and Tang, L.-L. (2005). Gender differs: assessing a model of online purchase intentions in e-tail service. *International journal of service industry management, 16*(5), 416-435.

[16] Chong, A. Y.-L. (2013). Predicting m-commerce adoption determinants: A neural network approach. *Expert Systems with Applications, 40*(2), 523-530.

[17] Columbus, L. (2017). *Internet Of Things Market To Reach $267B By 2020*. Retrieved from https://www.forbes.com/sites/louiscolumbus/2017/01/29/internet-of-things-market-to-reach-267b-by-2020/#72c5e804609b

[18] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.

[19] Davis, F. D., Bagozzi, R. P., and Warshaw, P. R. (1989). User acceptance of computer technology: a comparison of two theoretical models. *Management science, 35*(8), 982-1003.

[20] Dimitrov, D. V. (2016). Medical internet of things and big data in healthcare. *Healthcare informatics research, 22*(3), 156-163.

[21] Dodds, W. B., Monroe, K. B., and Grewal, D. (1991). Effects of price, brand, and store information on buyers' product evaluations. *Journal of marketing research*, 307-319.

[22] ENISA (2017). *Baseline Security Recommendations for IoT in the context of Critical Information Infrastructures*. Retrieved from https://doi.org/10.2824/03228

[23] Gao, L., and Bai, X. (2014). A unified perspective on the factors influencing consumer acceptance of internet of things technology. *Asia Pacific Journal of Marketing and Logistics, 26*(2), 211-231.

[24] Goswami, A., and Dutta, S. (2015). Gender differences in technology usage—a literature review. *Open Journal of Business and Management, 4*(01), 51.

[25] Grewal, D., Krishnan, R., Baker, J., and Borin, N. (1998). The effect of store name, brand name and price discounts on consumers' evaluations and purchase intentions. *Journal of retailing, 74*(3), 331-352.

[26] Hair Jr, J. F., Hult, G. T. M., Ringle, C., and Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage Publications.

[27] Han, C., and Yang, S. (2010). Value-based adoption of mobile banking service: a multi-channel perspective. Paper presented at the *Information Networking and Automation (ICINA), 2010 International Conference on*.

[28] Han, J., Kang, S., and Moon, T. (2013). An empirical study on perceived value and continuous intention to use of smart phone, and the moderating effect of personal innovativeness. *Asia Pacific Journal of Information Systems, 23*(4), 53-84.

[29] Hsu, C.-L., and Judy, C.-C. L. (2018). Exploring Factors Affecting the Adoption Of Internet of Things Services. *Journal of Computer Information Systems, 58*(1), 49-57.

[30] IBM (2018). *Quantum Computing - IBM Q - US*. Retrieved from https://www.research.ibm.com/ibm-q/

[31] Kim, E. (2018). *Amazon Echo owners spend more on Amazon than Prime members*. Retrieved from https://www.cnbc.com/2018/01/03/amazon-echo-owners-spend-more-on-amazon-than-prime-members.html

[32] Kim, H.-W., Chan, H. C., and Gupta, S. (2007). Value-based adoption of mobile internet: an empirical investigation. *Decision support systems, 43*(1), 111-126.

[33] Kim, K. J., and Shin, D.-H. (2015). An acceptance model for smart watches: Implications for the adoption of future wearable technology. *Internet Research, 25*(4), 527-541.

[34] Ko, E., Kim, E. Y., and Lee, E. K. (2009). Modeling consumer adoption of mobile shopping for fashion products in Korea. *Psychology & marketing, 26*(7), 669-687.

[35] Kowatsch, T., and Maass, W. (2012). Critical privacy factors of internet of things services: an empirical investigation with domain experts. *Knowledge and Technologies in Innovative Information Systems* (pp. 200-211): Springer.

[36] Kulviwat, S., Bruner II, G. C., and Al-Shuridah, O. (2009). The role of social influence on adoption of high tech innovations: The moderating effect of public/private consumption. *Journal of Business Research, 62*(7), 706-712.

[37] Kuo, Y.-F., Wu, C.-M., and Deng, W.-J. (2009). The relationships among service quality, perceived value, customer satisfaction, and post-purchase intention in mobile value-added services. *Computers in human behavior, 25*(4), 887-896.

[38] Kwon, H.-K., and Seo, K.-K. (2013). Application of value-based adoption model to analyze SaaS adoption behavior in Korean B2B Cloud Market. *International Journal of Advancements in Computing Technology, 5*(12), 368.

[39] Lin, T.-C., Lee, C.-K., and Lin, J. C.-C. (2010). Determinants of Enterprise 2.0 adoption: A value-based adoption model approach. Paper presented at the *Information Society (i-Society), 2010 International Conference on*.

[40] Lin, T.-C., Wu, S., Hsu, J. S.-C., and Chou, Y.-C. (2012). The integration of value-based adoption and expectation–confirmation models: An example of IPTV continuance intention. *Decision support systems, 54*(1), 63-75.

[41] Miniwatts Marketing Group (2017). *World Internet Users Statistics and 2017 World Population Stats*. Retrieved from http://www.internetworldstats.com/stats.htm

[42] Nysveen, H., Pedersen, P. E., and Thorbjørnsen, H. (2005). Explaining intention to use mobile chat services: moderating effects of gender. *Journal of consumer Marketing, 22*(5), 247-256.

[43] OECD (2018). *Internet access*, OECD Data. Retrieved from https://doi.org/10.1787/69c2b997-en.

[44] Pătru, I.-I., Carabaş, M., Bărbulescu, M., and Gheorghe, L. (2016). Smart home IoT system. Paper presented at the *RoEduNet Conference: Networking in Education and Research, 2016 15th*.

[45] Qian, Z.-H., and Wang, Y.-J. (2012). IoT technology and application [J]. *Acta Electronica Sinica, 5*, 026.

[46] Roostika, R. (2012). Mobile internet acceptance among university students: A value-based adoption model. *International Journal of Research in Management & Technology, 2*(1), 21-28.

[47] Sarstedt, M., Henseler, J., and Ringle, C. M. (2011). Multigroup analysis in partial least squares (PLS) path modeling: Alternative methods and empirical results. *Measurement and research methods in international marketing* (pp. 195-218): Emerald Group Publishing Limited.

[48] Sharma, R., and Mishra, R. (2014). A Review of Evolution of Theories and Models of Technology Adoption. *Indore Manag. J, 6*(2), 17-29.

[49] Statista (2018). *IoT: number of connected devices worldwide 2012-2025*. Retrieved from https://www.statista.com/statistics/471264/iot-number-of-connected-devices-worldwide/

[50] Symantec (2016). *IoT devices being increasingly used for DDoS attacks*. Retrieved from https://www.symantec.com/connect/blogs/iot-devices-being-increasingly-used-ddos-attacks

[51] Thelwall, M. (2008). Social networks, gender, and friending: An analysis of MySpace member profiles. *Journal of the Association for Information Science and Technology, 59*(8), 1321-1330.

[52] Transparency Market Research (2017). *Smart Homes Market (Application - Lighting Control, Security and Access Control, HVAC Control, and Entertainment Control) - Global Industry Analysis, Size, Share, Growth, Trends and Forecast 2017 - 2025*. Retrieved from https://www.transparencymarketresearch.com/smart-homes-market.html

[53] Venkatesh, V., and Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social

influence, and their role in technology acceptance and usage behavior. *MIS quarterly*, 115-139.

[54] Venkatesh, V., Morris, M. G., and Ackerman, P. L. (2000). A longitudinal field investigation of gender differences in individual technology adoption decision-making processes. *Organizational behavior and human decision processes, 83*(1), 33-60.

[55] Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.

[56] Venkatesh, V., Thong, J. Y., and Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, 157-178.

[57] Voicebot.ai(2018). *Smart Speaker Consumer Adoption Report 2018*. Retrieved from https://voicebot.ai/download-smart-speaker-consumer-adoption-report-2018/

[58] Wang, H.-Y., and Wang, S.-H. (2010). Predicting mobile hotel reservation adoption: Insight from a perceived value standpoint. *International Journal of Hospitality Management, 29*(4), 598-608.

[59] Xu, B., Da Xu, L., Cai, H., Xie, C., Hu, J., and Bu, F. (2014). Ubiquitous data accessing method in IoT-based information system for emergency medical services. *IEEE Transactions on Industrial Informatics, 10*(2), 1578-1586.

[60] Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: a means-end model and synthesis of evidence. *The Journal of marketing*, 2-22.

<Appendix A> Final Questionnaire

Disqualification Question*

This survey is strictly for people who have used the voice-activated smart speaker Amazon Echo. Have you either used or own this gadget personally?

*Yes *No

NOTE TO THESIS EVALUATORS: Skip logic sends respondent to disqualification page if the answer is no.

What is your gender? *

*Male *Female

What age group do you belong to? *

*Under 19 *20-29 *30-39 *Over 40

How long have you been using Amazon Echo? *

*Less than 1 year *1-3 years *over 3 years

In order of usage, to what extent to you use Amazon echo for these functions? *

	Never Used	Often Used	Used Frequently
Listening to Music			
Smart home control - lights, coffee-maker etc.			
Listening to a book or article			
Schedule arrangement			
Shopping			
Seeking of general information			

<Appendix A> Final Questionnaire (Cont.)

List of items by construct
< **Perceived Usefulness** > 1. Using Amazon Echo improves my work/life performance. 2. Using Amazon Echo enhances my work effectiveness and lifestyle. 3. Using Amazon Echo enables me to accomplish my task more quickly. 4. Using Amazon Echo help me get information useful for my work and personal life.
< **Perceived Enjoyment** > 1. While using Amazon Echo, I experience pleasure. 2. The process of using Amazon Echo is enjoyable. 3. I obtain fun from using Amazon Echo.
< **Perceived Security Risk** > 1. There is a security risk involved in using Amazon Echo. 2.There is too much security uncertainty associated with using Amazon Echo. 3. My decision to use Amazon Echo exposes me to security risks. 4. Using Amazon Echo would lead to a loss of privacy.
< **Perceived Technicality**> 1. It is not easy to make use of amazon echo. 2. It is not easy to learn how to utilize Amazon echo. 3. I find my interaction with amazon echo quite unclear and not understandable.
< **Perceived Cost** > 1. The cost I must bear for the use of Amazon Echo is too high. 2. The cost I must bear for the use of Amazon Echo is not reasonable. 3. I am not pleased with the cost I must bear for the use of Amazon Echo.
< **Social Influence**> 1. People who are important to me would recommend using Amazon echo. 2. People who are important to me would find using Amazon echo beneficial. 3. People who are important to me would find using Amazon echo a good idea. 4. It is expected that people like me use amazon echo.
< **Perceived Value**> 1. Compared to the fee I need to pay; the use of Amazon echo offers value for money. 2. Taking all the pros and cons into consideration, the use of Amazon echo is beneficial to me. 3. Compared to the time and effort I need to put in, the use of Amazon echo is beneficial to me. 4. Overall, the use of Amazon Echo gives me good value.
< **Adoption Intention**> 1. I intend to keep using Amazon Echo in the future. 2. I intend to continue using Amazon Echo. 3. I intend to recommend the use of Amazon Echo to my friends in the future.

◆ About the Authors ◆

Temidayo Oluwapelumi Shofolahan

Temi earned his bachelor's degree in statistics at the University of Agriculture, Abeokuta, Nigeria and obtained his master's degree in MIS at Ajou University, South Korea where he was a 2015 scholar of the Korean Government Scholarship Program. Temi now works in the private sector developing software applications while also pursuing his research interests in the area of Information system adoption, Electronic business and Smart computing.

Juyoung Kang

Professor Juyoung Kang is currently a Full Professor of e-Business at School of Business, Ajou University. She received her Ph.D. in Management Engineering from Korea Advanced Institute of Science and Technology (KAIST) in 2005. She has more than 50 refereed publications in academic journals and conference proceedings and has developed Intelligent Systems and E-Commerce applications with various industrial partners. Her current research interests are in the fields of text mining, cloud computing, big data, and intelligent systems. and etc.

Submitted: April 23, 2018; 1st Revision: June 17 2018; Accepted: November 21, 2018