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Hey Alexa … examine the variables influencing the use of artificial intelligent in-home voice assistants

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ABSTRACT

Artificial Intelligent (AI) In-home Voice Assistants have seen unprecedented growth. However, we have little understanding on the factors motivating individuals to use such devices. Given the unique characteristics of the technology, in the main hands free, controlled by voice, and the presentation of a voice user interface, the current technology adoption models are not comprehensive enough to explain the adoption of this new technology. Focusing on voice interactions, this research combines the theoretical foundations of U&GT with technology theories to gain a clearer understanding on the motivations for adopting and using in-home voice assistants. This research presents a conceptual model on the use of voice controlled technology and an empirical validation of the model through the use of Structural Equation Modelling with a sample of 724 in-home voice assistant users. The findings illustrate that individuals are motivated by the (1) utilitarian benefits, (2) symbolic benefits and (3) social benefits provided by voice assistants, the results found that hedonic benefits only motivate the use of in-home voice assistants in smaller households. Additionally, the research establishes a moderating role of perceived privacy risks in dampening and negatively influencing the use of in-home voice assistants.

1. Introduction

Artificial Intelligence (AI) has become an important topic amongst individuals and firms over recent years (Guzman, 2018), particularly given the growth of Voice Assistants (VAs). AI powered Voice Assistants including Amazon's *Echo*, Google's *Google Assistant*, Microsoft's *Cortana* and Apple's *Siri* have all contributed to the changing way in which individuals consume content, complete tasks, search for information, purchase products and interact with firms. McCue (2018) highlights that 27% of the global online population is using voice search, while it is predicted in-home voice assistants will see a growth of 1000% from 2018 to 2023 (Juniper & Research, 2018). Accordingly, Gartner (2016) estimates that voice assistants will replace other technology such as PCs and laptop computers for many utilitarian shopping activities.

While concerning for some individuals, voice assistants are always in *listening-mode* and are activated upon hearing a key word (also known as a 'wake-word') to commence its functionality (e.g. *Okay Google*, or *Hey Alexa*). Upon consuming the key word, the device is ready to interact with its user. The voice assistant uses natural language processing and machine learning to interpret and understand the language of the user and processes a response all within real time (Hoy, 2018). Therefore, due to the sophisticated programming of this technology, voice assistants are able to engage in complex dialog with an individual and execute multiple user requests. Given the overwhelming growth of voice-based technology, many individuals are communicating with voice assistants as part of their everyday life in the same way as they would with other humans (Sundar et al., 2017). Voice powered AI technology and individuals' interactions with them is a timely and important area of research given the limited understanding we have on why individuals interact with in-home voice assistants and the proliferation of the technology.

The introduction of voice assistants on mobile devices provided individuals with the first opportunity to interact with AI in a useful and meaningful form (Guzman, 2018). However, in-home assistants, such as Amazon's *Echo* device has further improved the interaction individuals can have with AI technology due to the advanced natural language processing and machine learning capabilities inherent within in-home voice assistants. While human-computer interaction scholars (e.g. Nass & Moon, 2000) have studied how individuals respond and behave towards machines, including voice-based technologies (Nass & Brave, 2005), the communication abilities of AI voice assistants are far more advanced than earlier voice-controlled human-computer interaction (Guzman, 2018). Primarily, such advancements are due to the implementation of natural language processing that allows individuals to

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speak to and receive in-context replies from a computer in a similar way to individuals' interactions with other human counterparts. Machine learning inherent in AI technology, which involves using algorithms and statistical models to perform tasks and make predictions without following explicit instructions or being programmed to perform the specific task, has the capability to learn user preferences and the topics the user is interested in (Bishop, 2006). Thus, in-home voice assistants are designed to be more human-like than previous attempts and intended to be an important part of an individual's everyday life, assisting with everyday life tasks such as turning lights on and off, setting alarms, understanding a user's schedule, looking up recipes, providing customised news information, checking on orders, purchasing items to name just a few useful functions.

Despite the attention given to in-home voice assistants and the proliferation of their adoption as well as their estimated future growth, there is little academic research exploring what influences individuals' use of voice technology. Given that voice assistants provide an alternative type of interaction that is often hands free and controlled by voice, the characteristics of the technology differ from other technologies such as websites and mobile apps, as such, the existing theoretical models explaining adoption and use of technology (i.e. TAM, UTAUT) may not comprehensively explain individuals' use of voice assistants. This research furthers our understanding in this domain through taking a Uses and Gratification theory (U&GT) approach to understanding the use of voice assistants focusing on voice interactions, while also integrating Human-Computer Interaction (HCI) literature on the social attributes of the system and individuals' perceived privacy risks.

1.1. Literature review

Given the rise of smart technologies, individuals have recently adopted an 'always on' online mentality which has become somewhat ubiquitous (Rauschnabel, He, & Ro, 2018). The smartphone device was the facilitator of this mentality, quickly followed by tablet devices, smartwatches and other wearable technology (Chuah et al., 2016). Thus, many individuals arrive at the introduction of the in-home voice assistant with the experience of adopting and using multiple smart technologies.

Voice assistants often provide a range of ways to interact with the device, for example, through the use of a mobile application (Alexa app available on the Apple store and the Play store), tactile buttons on the device itself and most notably via voice. With the use of voice interaction, AI voice assistants are arguably changing traditional forms of human-computer interaction (Feng, Fawaz, & Shin, 2017). Accordingly, they are adapting how individuals' retrieve information from websites and generally how they search for information (Hoy, 2018). Thus, voice assistants provide individuals with a convenient form of interaction with technology (Guzman, 2018) as users are not always required to physically input or interact with the device, instead they are provided with a more human like experience and can interact via voice (Alepis & Patsakis, 2017). Importantly, individuals do not need to stop their current task to interact via voice, enabling them to multi-task (Nass & Brave, 2005; Strayer, Cooper, Turrill, Coleman, & Hopman, 2017). Thus, the convenience offered by voice assistants is unmatched by any other technological system, allowing individuals to complete tasks with little effort on their part and without the need to type, read or hold a device (Hoy, 2018).

1.2. Adoption of technology

The Technology Acceptance Model (TAM) originally developed by Davis (1989) has been extensively used over recent years to understand the adoption and use of new technologies. The prominence of the TAM model is noted in the hundreds of articles across numerous disciplines in which TAM has been used to understand technology adoption (Rese, Baier, Geyer-Schulz, & Schreiber, 2017). Davis (1989) outlined that the drive to use technology can be explained by an individual's attitudes towards the technology along with its perceived usefulness and perceived ease of use. Meta analyses found that the perceived usefulness and perceived ease of use explains around 40% of the variance in an individual's behavioural intention to use a technology (Legris, Ingham, & Collerette, 2003). Accordingly, criticisms have been aimed at TAM due to the oversimplified view of technology adoption (San-Martin, Lopez-Catalan, & Ramon-Jeronimo, 2013). Thus, TAM2 (see: Venkatesh & Davis, 2000) and TAM3 (see: Venkatesh & Bala, 2008) were later introduced, incorporating additional variables, most notably, social norms (TAM2) and enjoyment (TAM3).

Furthermore, the Unified Theory of Acceptance and Use of Technology (UTAUT) provides an alternative theoretical understanding of technology adoption and use (see: Venkatesh, Morris, Davis, & Davis, 2003). Utilising numerous variables from TAM and extended versions (i.e. TAM2 & TAM3), UTAUT incorporates *effort expectancy*, *performance expectancy*, *social influence* and *facilitating conditions*, which are all moderated by *age*, *gender*, *experience*, and *voluntariness of use*; in influencing intention to use a technology. Subsequent versions of UTAUT, namely, UTAUT2 also include *hedonic motivation*, *price value* and *habit* (see: Venkatesh, Thong, & Xu, 2012). The motivation to develop the UTAUT model was to integrate the numerous overlapping variables used to explain technology adoption and to create a 'unified' theoretical basis (Williams, Rana, Dwivedi, & Lai, 2011). Thus Venkatesh et al. (2012) aimed to provide researchers a model that could be applied to understand the adoption and use of any technology. However, despite the efforts of the UTAUT model and its extension to provide a unified theoretical basis, criticisms have been leveraged at the model. Bagozzi (2007) critiqued the theory by arguing that a model with 41 independent variables for predicating intentions and a further eight variables for predicating behaviour reaches saturation and thus becomes of little help in informing technology adoption and use. Additionally, Van Raaij and Schepers (2008) further criticise the UTAUT model, pointing out that the explained variance in the model is only high when moderating key relationships with four variables. Thus, while both TAM and UTAUT have been extensively used to understand technology adoption and use, criticisms have been aimed at both. Additionally, given the unique attributes of Artificial Intelligent technology, such models may not encompass the motivations for adopting and using advanced technology. Thus, U&GT may provide a useful theoretical underpinning to advance our understanding in this new technological territory.

1.2.1. Uses and Gratification theory

U&GT is a theoretical motivational paradigm (Katz, Blumler, & Gurevitch, 1974) that can be used to understand individuals' motivations to adopt technology (Grellhesl & Punyaunt-Carter, 2012). The theory is grounded in communication science and has been used to understand why individuals seek the use of specific media or technology to satisfy their needs (Gallego, Bueno, & Noyes, 2016). U&GT combines social and psychological attributes of needs (Wurff, 2011). The theory proposes that individuals are goal oriented and select media that fits their needs (Katz et al., 1974). Luo and Remus (2014) outline that the theory can be considered axiomatic as it can be applied to almost every type of media. Accordingly, it has been applied in traditional media such as radio, television and newspapers (Bantz, 1982; Leung & Wei, 1998), and interactive media including the Internet and websites (Flanagin & Metzger, 2001), social networks (Osei-Frimpong & McLean, 2018), online games (Wu, Wang, & Tsai, 2010), virtual and augmented reality (Rauschnabel, Rossmann, & Dieck, 2017; 2018). U&GT can therefore be applied to understanding individuals' choice to partake in the use of in-home voice assistants as they are likely motivated by their desire to gratify a range of needs. Accordingly, U&GT provides an interesting theoretical lens to understand the motivations towards using AI powered in-home voice assistants (such as Google's *Google Assistant* and Amazon's *Echo*).

While individuals' needs will vary based on unique characteristics and situations, researchers have attempted to catalogue needs and gratifications (Katz et al., 1974). Most recently, Rauschnabel et al. (2018) outline three categories, including utilitarian benefits, hedonic benefits and symbolic benefits. From a utilitarian perspective, individuals may use a voice assistant for information gathering to learn about a topic or to complete a task. From a hedonic benefits perspective, individuals may use a voice assistant to seek enjoyment from the activity. Thirdly from a symbolic benefits perspective, individuals may use specific media to reaffirm their social status, for example some individuals may want to appear technologically advanced and savvy through using a voice assistant. However, Rauschnabel et al. (2018) overlooked the additional category, namely, social benefits, referring to the idea that individuals use specific media for social needs. Prior research has outlined the social benefits in applying U&GT to social media (Osei-Frimpong & McLean, 2018) and in online games (Wu et al., 2010). Osei-Frimpong and McLean (2018) as well as Wu et al. (2010) found that the social presence of others and the social attraction of others motivated individuals to engage in social media. Thus, drawing on the aforementioned technology theories and U&GT we propose that four key categories may motivate use of in-home voice assistants, (1) Utilitarian Benefits, (2) Hedonic Benefits, (3) Symbolic Benefits and (4) Social Benefits. Section 3.0 outlines our rationale.

1.3. Privacy risks

While voice assistants provide benefits to their users, continued advancements in technology can pose threats to individuals' privacy (Alepis & Patsakis, 2017). Collier (1995) outlines that privacy risks in relation to technology refers to the perceived threat to an individual's privacy due to the increased level of information that technology gathers on individuals beyond the individual's knowledge and sometimes control. Given that technology has become a central part of an individual's everyday life, particularly in the case of in-home voice assistants, privacy concerns among individuals continues to grow (Hoy, 2018). Lei et al (2018) outline that voice assistants such as the Amazon Echo have security vulnerabilities that can be exploited by hackers. Individuals shy away from talking about sensitive topics or using their voice assistants to make payments due to concerns over privacy (Moorthy & Vu, 2015). Sophisticated voice assistants can perform high priority commends utilising personal account details, make appointments, look up service information and place orders all on behalf of their user (Feng et al., 2017). Thus, voice assistants require an extensive set of software permissions to undertake their tasks, which individuals overwhelmingly provide (Alepis & Patsakis, 2017). Therefore, while voice assistants aid individuals in their everyday life, such benefits are accompanied by a new set of risks that can make individuals vulnerable to attacks on personal details (Lei et al. 2018).

2. Conceptual development

Given the change in the type of user interaction with voice assistants, individuals have limited interaction with a traditional user interface, instead they most often interact hands free with their voice (Hoy, 2018). Accordingly, as AI voice assistants have boundary crossing attributes, they differ from other existing technologies, as such, existing theoretical models (i.e. TAM & UTAUT) on their own may not be adequate in explaining behaviour towards the technology. Therefore, in consideration of the unique attributes of voice assistants, a combination of U&GT and HCI attributes with voice technology, along with the attitudinal dimension of perceived privacy risks may offer the required insight needed to understand the variables driving the use of in-home voice assistants.

2.1. Utilitarian benefits

Voice assistants have been conceptualised as offering individual's a useful and convenient way to complete tasks such as searching for information, purchasing repeat products or looking up customer service information (Hoy, 2018). HCI research has outlined the role of utilitarian factors in influencing the adoption of technology (Venkatesh et al., 2012). Recent research has outlined the role of advanced technology such as mobile apps in providing individuals with utilitarian benefits (McLean, Al-Nabhani, & Wilson, 2018). Given the aforementioned ability to use in-home voice assistants hands free without the need to interact with a physical user interface (rather a voice interface) and enabling individuals to multi-task during interactions, we posit that the subsequent usefulness and convenience provided by in-home voice assistants will influence their use. Thus, we hypothesise:

H1. The utilitarian benefits from in-home voice assistants will have a positive influence on individuals' use of the technology.

2.2. Hedonic benefits

Previous research outlines that individuals interact with technology for hedonistic purposes (Wu et al., 2010). Hedonic benefits or attributes relates to the individual's emotional experience such as enjoyment and pleasure obtained from interacting or using new technology such as in-home voice assistants (Schuitema, Anable, Skippon, & Kinnear, 2013). Similarly, Venkatesh et al. (2012) further point to the role of enjoyment in influencing individuals to adopt and use technology. TAM2 and the UTAUT posit that enjoyment can influence the use of technology, however this can be context dependent (Venkatesh et al., 2012). Previous research from the online shopping environment suggests that consumers who do not experience enjoyment during their shopping encounter will unlikely use the service again in the future (Martin, Mortimer, & Andrews, 2015). Fang (2018) points out that while utilitarian benefits are fundamental to mobile app adoption and use, hedonic motivation to use them is fundamental in the success of apps. Similarly, while prior research conceptualises the utilitarian benefits of voice assistants (Hoy, 2018), we suggest that hedonic motivations will be key to the success and continued use of in-home voice assistants. Thus we hypothesise:

H2. The hedonic benefits from in-home voice assistants will have a positive influence on individuals' use of the technology.

2.3. Symbolic benefits

Symbolic benefits refer to the extent to which an individual perceives to gain a symbolic reward such as making a favourable impression on others (Goodin, 1977). In part, this also relates to an individual's "sense of self or social identity" resulting from the adoption or use of new technology (Schuitema et al., 2013). Hence, previous research has outlined the role of *image* in influencing the adoption of technology (King & He, 2006), to the extent that an individual may believe that the association with or use of the technology enhances their social status. Wilcox, Kim, and Sen (2009) affirm that individuals often purchase luxury items for symbolic purposes to enhance social status. From a technology point of view, Rauschnabel et al. (2018) found that the symbolic benefits derived from wearable technology (smart-glasses) influenced individuals' intention to use the technology. This view is also shared by Selwyn (2003), who avers that individuals incorporate technology use in their daily life as a result of the symbolic value they achieve in such an activity. In a similar vein, individuals may use in-home voice assistants to enhance their image and social status. Thus we hypothesise:

H3. The symbolic benefits from in-home voice assistants will have a positive influence on individuals' use of the technology.

2.4. Social benefits

Individuals have expressed their eagerness to talk to computers since the first commercial computer was introduced (Hoy, 2018). Drawing on robotics research, it is apparent that there is a growing level of social presence from machines (Chattaraman, Kwon, Gilbert, & Ross, 2018). Automated social presence is the extent to which machines make individuals feel as though they are in the presence of another social entity (Heerink, Krose, Evers, & Wielinga, 2010). Short, Williams, and Christie (1976) define social presence as the degree of salience of the other person in an interaction. The works of Nass and colleagues (see Fogg & Nass, 1997; Nass & Brave, 2005; Nass & Moon, 2000; Reeves & Nass, 1996) provide insight into how individuals treat computers like a social entity. This body of research outlines that as computers use natural language, interact with users in real-time and in some cases fulfil traditional human operated social roles (e.g. customer service in a Bank), even advanced computer users often treat machines as social entities (Lombard & Ditton, 2000). Moon (2000) posits that humans are socially oriented beings, and thus apply social roles when interacting with technology such as politeness, pausing for response and curtsy during interactions in the same way as they would with another human. Lombard's research (1995; 2000) found that as computers can mimic human-like attributes, these attributes such as voice, appearance, and mannerisms can act as cues that evoke social responses. Drawing on this, Li (2015) points out that human like attributes elicit social responses. For example, language based conversations between individuals and AI powered devices serve as an important human-like attribute that elicits a sense of social presence in the mind of the individual. As individuals become comfortable in their conversations with an artificial personification, similar to conversations with other humans, they develop a rapport with the artificial assistant (Cerekovic, Aran, & Gatica-Perez, 2017). Cialdini (2007) suggests that individuals are more likely to be socially attracted to others with a pleasant demeanour, increasing their social attractiveness. Sundar, Jung, Waddell, and Kim (2017) outline that robots can provide a sense of companionship while assisting their users. Thus, according to the MAIN model (Sundar, 2008), this can elicit the heuristic of social presence and social attractiveness. Accordingly, such social presence and social attractiveness may motivate individuals to engage with the AI technology in the same way as they would with other human counterparts (Chattaraman et al., 2018; Sundar et al., 2017). Therefore, we hypothesise:

H4. The social presence from in-home voice assistants will have a positive influence on individuals' use of the technology.

H5. The social attractiveness from in-home voice assistants will have a positive influence on individuals' use of the technology.

2.5. Moderating effect of privacy risks

With the advancement in technology, privacy risks have been centre of attention with many new smart technologies (e.g., Wearable Technology: See Rauschnabel et al., 2018). Privacy risks have been conceptualised as having a dampening effect on individuals' adoption and use of voice assistant technology (Hoy, 2018). Hardware and software providers such as Google and Amazon have taken recent steps to include *voice printing*, which uniquely identifies the user of the device and stops the voice assistant from detailing personal information. Additionally, such systems have also introduced password controlled access to purchasing products. Yet, despite such attempts, privacy risks appear to have an influence on individual's attitudes towards the device (O'Flaherty, 2018; Feng et al., 2017). While individuals may derive benefits from their use of their voice assistant, such benefits may be reduced by the perceived privacy risks of stolen personal details, stolen financial details and seemingly unsecure private conversations. Thus we hypothesise:

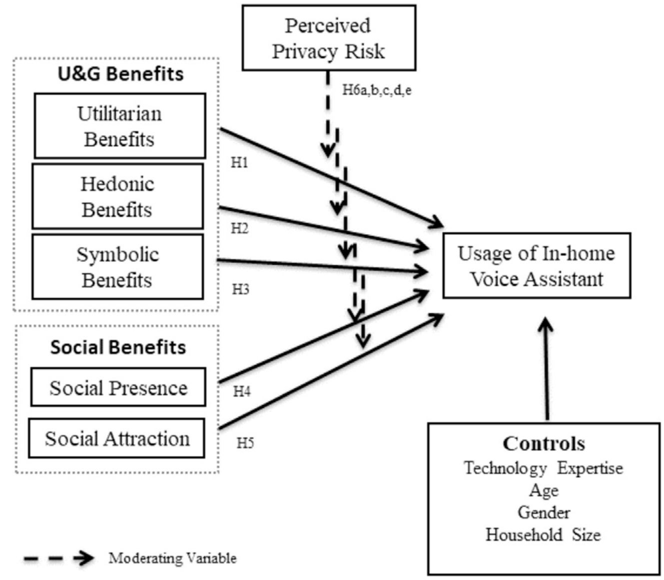

Fig. 1. Hypothesised model.

H6. Perceived privacy risks will have a moderating negative effect on:

a) the utilitarian benefits of in-home voice assistants influencing individuals' use of the technology.
b) the hedonic benefits of in-home voice assistants influencing individuals' use of the technology.
c) the symbolic benefits of in-home voice assistants influencing individuals' use of the technology.
d) the social presence benefits of in-home voice assistants influencing individuals' use of the technology.
e) the social attractiveness benefits of in-home voice assistants influencing individual's use of the technology.

Following the conceptual development discussions, Fig. 1 provides a pictorial representation of our hypothesised relationships. The hypothesised model also illustrates four control variables, namely, technology expertise, age, gender and household size.

2.6. Methodology

An online questionnaire using the Qualtrics platform was used to gather the data to test the hypothesised model in Fig. 1. The research was limited to the Amazon Echo in-home voice assistant due to the large adoption rate of the device. At the time of writing, the Amazon Echo in-home voice assistant offered users the most advanced set of capabilities and largest range of '*skills'* (i.e.: applications - branded and non-branded) to add to the Echo device. Over 50,000 unique branded '*skills'* can be added to the Amazon echo including the *Uber* skill to order a cab, *United Airlines* skill to check flight information and the *Lonely Planet* skill to learn about destinations (Kinsella, 2018).

Data were gathered from 766 consumers in the UK with the use of a market research firm's panel. Respondents were offered a small financial incentive to take part in the research. Following data cleansing and removing those responses that contained missing values, the sample consisted of 724 responses. Respondents had used the device for at least one month to provide insight into the variables motivating the use of the in-home voice assistant, this information was collected following an initial screening question in the questionnaire. Table 1 provides an overview of the study's respondents.

The scales used in the research were drawn and adapted from scales

Table 1
Details of respondents.

Characteristics	Number (n)	Percentage
Gender		
Female	401	55
Male	323	45
Age Groups		
18–24	55	8
25–34	240	33
35–44	207	29
45–54	153	21
55–64	69	9
Education		
High-School Graduate	280	39
College Degree	140	19
University Degree	193	27
No Formal Qualification	111	15
Technology Expertise		
Very Experienced	211	29
Experienced	309	43
Average User	165	23
Not Experienced	39	05
Household Size		
One – Two Persons	398	55
Three Persons and above	326	45

in the extant literature. 6 variables utilising a 7 point Likert scale (Strongly Disagree – Strongly Agree) were used to measure Utilitarian Benefits, Hedonic Benefits, Symbolic Benefits, Social Attractiveness, Usage of In-Home Voice Assistants and Perceived Privacy Risk. A new scale was developed to measure Social Presence, drawing upon the previous works of Lee, Peng, Jin, and Yan (2006), Nowak (2013) and Nass and Moon (2000). Table 2 outlines the items of each scale.

2.7. Preliminary analysis

A range of preliminary analyses were calculated. As shown in Table 2, Cronbach's alpha coefficient was calculated to assess the reliability of the scales used in the study. Each scale exceeded the value of 0.7 affirming the scales are reliable indicators of their corresponding variables (See Pallant, 2013 for critical values). Given the introduction of the scale *Social Presence,* an Exploratory Factor Analysis (EFA) was conducted which illustrated a KMO sampling adequacy of 0.788 and a corresponding *p*-value < .0001 for Bartlett's Test of Sphericity, a further Confirmatory Factor Analysis (CFA) showed *goodness of fit* for the scale.

Furthermore, in order to test the hypothesised model in Fig. 1, structural equation modelling (SEM) in AMOS Graphics was used. SEM allows the hypothesised relationships to be tested in a simultaneous analysis. However, SEM is a two-part process. First, a confirmatory factor analysis (CFA) of the entire model is performed. The CFA outlines the causal relationships in the model. The results of the CFA affirm *goodness of fit* in the data: $x^2_{(317)} = 824.670$, $\rho = 0.001$, $x^2/df = 2.60$; RMSEA = 0.047, RMR = 0.018, SRMR = 0.045, CFI = 0.9692, NFI = 0.961, GFI = 0.951. In addition, each of the regression values were adequate and showed statistical significance ($p < .05$).

Further analysis satisfied convergent and discriminant validity following Fornell and Larcker (1981). The results illustrated in Table 3 present the average variance extracted (AVE) values all above 0.50 and construct reliabilities > 0.70. Accordingly, the AVE values were also greater than the square of their correlations, thus supporting discriminant validity.

Prior to the second step in the SEM process, estimating the structural model, common method bias and multicollinearity tests were calculated. Such tests help to avoid misleading conclusions from the data. To examine if any common method bias (CMB) exists, a common latent factor was presented with all indictors of the variables included in the model. The common later factor outlined a value of .549. This

Table 2
Scale items.

Variable	Reference	Scale Items	Cronbach's Alpha
Hedonic Benefits	Adapted from: Davis et al. (1992)	• I find using my voice assistant to be enjoyable • The actual process of using my voice assistant is entertaining • I have fun using my voice assistant to complete tasks.	.869
Utilitarian Benefits	Adapted from: Taylor and Todd (1995)	• Using my voice assistant is a convenient way to manage my time. • Completing tasks with my voice assistant makes my life easier. • Completing tasks with the voice assistant fits with my schedule • Completing tasks with the voice assistant is an efficient use of my time	.779
Symbolic Benefits	Adapted from: Moore and Benbasat (1991)	• Using my in-home voice assistant enhances my image amongst my peers • Using my in-home voice assistant makes me seem more valuable amongst my peers • Using my in-home voice assistant is a status symbol for me • Using my in-home voice assistant makes me seem more prestigious than those who do not	.805
Social Presence	Newly Developed Scale	• When I interact with the voice assistant it feels like someone is present in the room • My interactions with the voice assistant are similar to those with a human • During my communication with the voice assistant I feel like I am dealing with a real person • I communicate with the voice assistant in a similar way to I communicate with humans	.841
Social Attraction	Lee et al. (2006)	• I think the voice assistant (Alexa) could be a friend of mine • I have a good time with the voice assistant (Alexa) • I would like to spend more time with the voice assistant (Alexa)	.874
Perceived Privacy Risk	Adapted from: Al-Debei et al. (2014)	• I have my doubts over the confidentiality of my interactions with the voice assistant • I am concerned to perform a financial transaction via the voice assistant • I am concerned that my personal details stored with the voice assistant could be stolen • I am concerned that the voice assistant collects too much information about me	.788
Usage of In-home Voice Assistants	Venkatesh et al. (2012)	• I plan to continue to use the in-home voice assistant in the future. • I intend to continue to use the in-home voice assistant in the future. • I predict I would continue to use the in-home voice assistant in the future.	.801

Table 3
Convergent and discriminant validity.

	CR	AVE	MSV	UB	HB	SB	SP	SA	UVA	PPR
Utilitarian Benefits (UB)	0.779	0.701	0.520	0.837						
Hedonic Benefits (HB)	0.869	0.634	0.531	0.339	0.796					
Symbolic Benefits (SB)	0.805	0.681	0.464	0.282	0.311	0.825				
Social Presence (SP)	0.841	0.656	0.477	0.216	0.167	0.193	0.809			
Social Attractiveness (SA)	0.874	0.722	0.524	0.197	0.204	0.241	0.411	0.849		
Use of In-home Voice Assistant (UVA)	0.801	0.598	0.543	0.374	0.311	0.276	0.281	0.307	0.773	
Perceived Privacy Risk (PPR)	0.788	0.701	0.499	0.204	0.289	0.232	0.323	0.276	0.349	0.847

CR - Construct Reliability; AVE – Average Variance Extracted; MSV - Maximum Shared Variance.

value is subsequently squared to provide a percentage value (0.301 = 30%). As the value presented falls below 50% (see: Ranaweera and Jayawardhena. 2014) it is unlikely that CMB exists.

Moreover, to assess multicollinearity each of the variables were assessed using the variance inflation factor (VIF) analysis. Given that the results outlined no variable above the critical value of 3.0 (Hair, 2010) it can be concluded that multi-collinearity was not violated.

2.8. Results of SEM

Following the aforementioned tests, the structural equation model was estimated testing the hypothesised relationships in Fig. 1. The structural model affirmed *goodness of fit*: ($x^2_{(30)}$ = 89.578, $p < .05$, x^2/df = 2.98, RMSEA = 0.052 (RMSEA Confidence Intervals: LO90 = 0.031, HI90 = 0.073), SRMR = 0.019, RMR = 0.020, CFI = 0.966, NFI = 0.959, GFI = 0.960) and shows support for some of the hypothesised relationships as outlined in Table 4.

The results from the structural equation model, as shown in Table 4, illustrate support for four hypotheses. The results indicate the importance of the utilitarian benefits motivating the use of an in-home voice assistant, thus supporting H1 (Utilitarian Benefits → Usage of in-home voice assistant; $\beta = 0.681^{***}$). Although, somewhat a weak relationship, the results also indicate support for H3 as Symbolic Benefits appear to motivate individuals to use an in-home voice assistant (Symbolic Benefits → Usage of in-home voice assistant; $\beta = 0.156^{**}$). Additionally, the 'social benefits', namely, Social Presence and Social Attraction have a strong effect in motivating individuals' use of in-home voice assistants (Social Presence → Usage of in-home voice assistant; $\beta = 0.721^{***}$; Social Attraction → Usage of in-home voice assistant; $\beta = 0.692^{***}$).

While the results indicate support for hypotheses H1, H3, H4, and H5. A non-significant result was found between Hedonic Benefits and Usage of an in home voice assistant (Hedonic Benefits → Usage of in-home voice assistant; $\beta = 0.142^{ns}$), thus affirming that individuals do not use a voice assistant for enjoyment or seek fun during interactions. Therefore, the research rejects H2.

The research also controlled for age, gender, technology expertise and household size. The results in Table 4 indicate a non-significant affect with exception to household size. Household size shows a positive significant relationship with usage of in-home voice assistants. We categorised house hold size as (1) occupied by one to two persons and (2) occupied by three or more persons. For the purpose of this analysis we labelled each category small household size (one to two persons) and large household size (three or more persons). Accordingly, given that in-home voice assistants are a feature of the household and the significant result, we further examined the effect of household size through multi-group analysis. Through using AMOS Graphics, multi-group analysis was selected, regression paths were named, bootstrapping was selected, where the bootstrapping confidence output illustrates the confidence interval between each household size. The results indicated a significant difference between Social Presence and Use of in-home voice assistants with regard to household size (Small Household: $\beta = .711$, $p = .001$; Large Household: $\beta = 0.377$, $p = .039$; difference = p.033). Additionally, a significant difference is found between Social Attractiveness and Use of a voice assistant (Small Household: $\beta = 0.695$, $p = .001$; Large Household: $\beta = 0.403$, $p = .030$; difference = p.041) as well as Hedonic Benefits and Use of a voice assistant (Small Household: $\beta = 0.279$, $p = .050$; Large Household: $\beta = 0.122$, $p = .113$; difference = p.026). These results will be discussed in more detail in subsequent sections.

2.9. Interaction moderation analysis

Moderation effect analysis was calculated to test the moderating role of perceived privacy risks and thus to test hypotheses H6 a, b, c, d and e. The moderating effects were assessed in the entire model using moderated SEM in AMOS Graphics (see: Xanthopoulou et al., 2007). In line with Ranaweera and Jayawardhena (2014) as well as Matear, Osborne, Garrett, and Gray (2002), new variables were created in IMB SPSS to examine the effects of the moderating variables. Firstly, the independent variable was adapted (e.g. Utilitarian Benefits) and the moderating variable (Perceived Privacy Risks) through mean centring. Accordingly, a new interactive term was created by multiplying the independent variable with the moderating variable, resulting in the interactive term: *Utilitarian Benefits X Perceived Privacy Risks*. Thus, for hypothesis H6a, the dependent variable (Use of in-home voice assistant) was regressed on the independent variable (Hedonic Benefits), the moderator (Perceived Privacy Risks), and the interactive term

Table 4
SEM standardised regression path analysis.

Hypotheses				Standardised Estimate β	t-value	R^2
H1	Utilitarian Benefits	→	Usage of in-home voice assistant	$.681^{***}$	3.88	.69
H2	Hedonic Benefits	→	Usage of in-home voice assistant	$.142^{ns}$	2.19	.69
H3	Symbolic Benefits	→	Usage of in-home voice assistant	$.156^{**}$	2.10	.69
H4	Social Presence	→	Usage of in-home voice assistant	$.721^{***}$	4.45	.69
H5	Social Attraction	→	Usage of in-home voice assistant	$.692^{***}$	3.12	.69
Controls						
	Technology Expertise	→	Usage of in-home voice assistant	$.097^{ns}$	1.69	.67
	Age	→	Usage of in-home voice assistant	$.105^{ns}$	1.51	.68
	Gender	→	Usage of in-home voice assistant	$.081^{ns}$	1.22	.66
	Household Size	→	Usage of in-home voice assistant	$.233^{**}$	2.39	.70

Table 5
Interaction moderation analysis.

Hypotheses				Standardised Estimate β	t-value	R^2	Effect
H6a	Utilitarian Benefits X Perceived Privacy Risks	→	Usage of in-home voice assistant	.368 **	3.12	.63	Dampening Effect
H6b	Hedonic Benefits X Perceived Privacy Risks	→	Usage of in-home voice assistant	-.213 **	−2.24	.63	Negative Effect
H6c	Symbolic Benefits X Perceived Privacy Risks	→	Usage of in-home voice assistant	-.111 **	−2.11	.63	Negative Effect
H6d	Social Presence X Perceived Privacy Risks	→	Usage of in-home voice assistant	.432 **	2.73	.63	Dampening Effect
H6e	Social Attraction X Perceived Privacy Risks	→	Usage of in-home voice assistant	.398 **	2.66	.63	Dampening Effect

Dampening Effect = a statistically significant reduction with the presence of the moderating variable, but not changing the positive relationship. Negative Effect = a significant negative relationship.

(Utilitarian Benefits X Perceived Privacy Risks). Thereafter, this process was repeated for H6b, c, d and e.

The results determine a significant interactive influence supporting each of the research hypotheses but with varying effect. Table 5 outlines the relationships with the presence of perceived privacy risks. The results indicate the important moderating role of perceived privacy risks in influencing individuals' behaviour.

While the utilitarian benefits and social benefits (social presence and social attraction) remain positively significant in influencing the use of an in-home voice assistant, the introduction of the moderating variable, perceived privacy risk, results in a reduction (dampening effect) of the significance of these variables motivating use in comparison with the results in Table 4. Thus, perceived privacy risk is a concern for individuals and a barrier to using the AI powered in-home voice assistant. The results also assert that the symbolic benefits of the voice assistant (i.e. enhancing one's image) are outweighed by the perceived privacy risks, resulting in a significant negative moderating effect between Symbolic Benefits and Usage of the in-home voice assistant. Lastly, the perceived privacy risk also further reduces the influence of hedonic benefits.

Furthermore, given the differences found in household size, further analysis of the moderating variable was conducted between 'small household size' and 'large household size'. The results indicate overall a stronger interaction effect on larger household sizes. The results pertain that for larger households, the *hedonic benefits* influence on use of the in-home voice assistant is negatively significant when the moderating variable of perceived privacy risk is present (Large Household: $\beta = -0.216$, $p = .037$; Small Household: $\beta = 0.127$, $p = .067$; difference = p.035), yet in a small household, the perceived privacy risks has no moderating effect. Moreover, a significant difference is found regarding both social benefits dimensions (Social Presence and Social Attraction). The results indicate that privacy risks have less effect on smaller households in comparison to larger households (*Social Presence*: Small Household: $\beta = 0.189$, $p = .419$; Large Household: $\beta = -0.122$, $p = .072$; difference = p.043; *Social Attraction*: Small Household: $\beta = 0.207$, $p = .381$; Large Household: $\beta = -0.158$, $p = .61$; difference = p.027). All other relationships showed no significant differences. The following sections will discuss the theoretical and practical implications of these results.

3. Discusssion

3.1. Theoretical implications

In-home voice assistants have grown in popularity over recent months and are forecasted for exceptional growth over the coming years, yet knowledge of the key success factors are unknown. This research makes an attempt to address this gap. Use of such devices in an individual's own personal space (i.e. their home) presents a new form of interaction with technology that is intended to be embedded as part of individuals' everyday life. Given the unique characteristics of the technology (hands free and controlled by voice), the current technology adoption models are not comprehensive enough to explain the adoption of this new technology. Thus in contributing to the extant literature, this research combines the theoretical foundations of U&GT with technology theories and HCI literature to gain a clearer understanding on the motivations for adopting and using in-home voice assistants. Therefore, this study presents a conceptual model on the use of voice controlled technology and an empirical validation of the model with users of in-home voice assistants. The validated model presents high explanatory power (R^2 0.69), with 69% of variance explained. In turn the research provides unique contributions to academic research in the field of technology adoption, human computer interaction, AI and marketing.

Firstly, we provide support for a new way to understand technology adoption and use of AI powered voice controlled technology through the identification of antecedents incorporating three dimensions, drawing upon U&GT. We find that individuals are motivated by the (1) utilitarian benefits, (2) symbolic benefits and (3) social benefits provided by voice assistants. Conversely, the hypothesised hedonic benefits do not motivate individuals' use of such technology. Accordingly, this provides insight into the purpose of using in-home voice assistants in order to complete goal driven tasks. Previous research (Martin et al., 2015; Venkatesh et al., 2012) outlined that hedonic benefits from technology are key to success. However, this research finds that individuals do not use voice assistants to seek fun or enjoyment. This may be due to the voice controlled user interaction that is void of supporting rich media such as images or videos. Thus, users turn to voice controlled technology due to their usefulness and convenience to aid them in the completion of tasks, accordingly influencing the continuous use of the technology.

Limited research has acknowledged the role of symbolic benefits influencing technology adoption and use. Wilcox et al. (2009) found that individuals often purchase items (particularly luxury items) to enhance their social status. Rauschnabel et al. (2018) were the first to explore symbolic benefits in relation to technology, focusing on the wearable technology, smart-glasses. This research finds a weak but significant relationship between the symbolic benefits and the use of in-home voice assistants. As AI technology has become more widely available, embedded as part of our everyday life and somewhat trendy to use, individuals may be adopting and using the technology to enhance their social status to make them appear important within their peer groups. Thus, in the same way individuals may furnish their home with designer hard and soft furnishings to elicit symbolic benefits, the in-home voice assistant may become part of this social enhancing activity.

Moreover, a unique characteristic of in-home voice assistants is their ability to convey strong social benefits in the form of social presence and social attractiveness. While technology in the past has been highlighted as conveying social presence, with individuals applying social rules to their interactions with computers (e.g. pausing for a response, showing politeness and curtsy during interactions), AI powered voice assistants convey one of the strongest humanlike attributes through the use of voice communication. Li (2015) outlined that voice interactions elicits the sense of social presence in the mind of an individual. Cerekovic et al. (2017) suggest that individuals converse with voice assistants in the same way as they do with other humans, developing a rapport with the artificial intelligent assistant. Accordingly, the results illustrate that such social presence conveyed by the voice assistant is a key factor to the success of the technology, thus motivating individuals to use the device. Given that voice assistants '*assist*' their users in a pleasant demeanour, such social attractiveness motivates consumers to interact with the technology. Alternative technologies do not convey such a humanlike social presence and thus technology adoption theories do not capture such a dimension in their explanation of technology adoption and use. Therefore, given the advancements in AI technology utilising natural language processing and machine learning to learn and understand their user's preferences, the social presence and attractiveness machines are able to convey is a new and important dimension of technology adoption and use.

The second major contribution of this research addresses the moderating role of perceived privacy risks. Prior research has outlined the continued concern of privacy risks due to the speed and diffusion of new technological innovations. Previous research has outlined that privacy concerns can reduce an individual's intention to adopt technology (Hoy, 2018). However, such technology does not contain the unique social presence and social attractiveness characteristics and advanced security of natural language processing and machine learning of voice assistants, whilst voice assistants are also used in the privacy of one's home. Additionally, Rauschnabel et al. (2018) could not confirm the effect of privacy concerns on an individual's intention to use smart wearable technology. However, our results outline a significant dampening effect of perceived privacy risks on utilitarian benefits and social benefits. Whilst utilitarian benefits, and social benefits (social presence and social attractiveness) remain statistically significant in influencing the use of in-home voice assistants, a significant dampening effect was found. Additionally, the perceived privacy risks have a significant negative effect on symbolic benefits to the extent that its influence on usage of a voice assistant becomes insignificant. Thus, the concerns of stolen person details, financial details and the perception of assistants listening to private conversations as conceptualised in the literature explains the dampening and negative effect of perceived privacy risks on the use of the technology.

Moreover, this research finds that the size of the household (Large versus Small) has an effect on the motivators and use of the voice assistant. Given that the voice assistant is a household item the findings further our understanding of use. Households with fewer occupants (2 or less) are more motivated to use a voice assistant due to the social benefits. This may be due to the additional social presence offered by the voice assistant, replacing interaction that may be had with a human counterpart in a larger household. Additionally, the results find that smaller households regard the hedonic benefits of the voice assistant (which was insignificant without the inclusion of household size) to motivate their use of the technology. Thus it may be possible that those households with fewer occupants may turn to their voice assistant to seek entertainment as well as social presence. Accordingly, individuals' interactions with an in-home voice assistant in a smaller occupied household may be used to replace the missing human interaction that is available in larger occupied households. This possible explanation is in line with Sunder et al. (2017) research that elderly individuals utilise artificial intelligent robots for companionship to avoid loneliness. However, it should be noted that such differences could be explained by household composition (households comprising of a mix of adults and children, adults only, couples and room-mates) rather than household size.

Moreover, privacy concerns appear to negatively influence households that have a larger number of occupants in comparison to those with a smaller number. Within larger occupied households, perceived privacy risks interferes with the social benefits (Social Presence and Social Attraction) in motivating the use of an in-home voice assistant. It could be possible that the perceived privacy risks may outweigh the social benefits, given that other human counterparts live in the household and therefore meet the social needs of an individual without the risks associated with using the voice assistant. On the contrary, the social benefits and hedonic benefits derived from interactions with a voice assistant by individuals in smaller occupied households is not interfered by perceived privacy risks. Thus, aligning with Sundar et al.'s (2018) research on AI companionship, such findings are possible indications of the social benefits provided by AI voice assistants for those who are possibly in need of social interaction. However, it should again be noted that such findings may be explained by household composition rather than household size.

3.2. Practical implications

Developers and producers of in-home voice assistants should continue to develop the social benefits that are derived from user interaction. As technological capabilities continue to advance and we have a better understanding of natural language processing and machine learning, developers and producers should focus on developing the humanlike conversations between the voice assistant and the human user. Machine learning inherent in AI technology has the capability to learn user preferences and the topics the user is interested in discussing, thus focusing on such technology to offer further social benefits will likely increase the number of individuals adopting and using the technology.

The findings of this study reveal that in-home voice assistants are used for utilitarian purposes. Thus, individuals are motivated to use in-home voice assistants to help them complete tasks, look up information, seek support and process orders. Developers that are developing *skills* (applications) to add to in-home voice assistants should focus on the utilitarian benefits that can be gained from their *skill*. Accordingly, brands should consider the utilitarian value that a branded *skill* could offer to individuals. Some branded *skills* focus on hedonic benefits, however, the results indicate that individuals are motivated to use their in-home voice assistants for goal directed tasks. Thus, branded *skills* that offer individuals convenience are more likely to be used. Additionally, brands should utilise the social benefits of the in-home voice assistant that is limited through other technology. Therefore, brands should focus on developing skills that enable the user to discuss a brand-related topic with the voice assistant that is of interest to the user. This offers brands the opportunity to learn about their customers' preferences and daily interactions within the intimate setting of the individual's own home.

Security and privacy issues are an important concern for individuals due to the speed of diffusion and adoption of new technologies. Based on our results, the perceived privacy risk of voice assistants has a significant negative effect on the gratifications motivating individuals to use the technology. Given the large set of software permissions voice assistants require to undertake their tasks, individuals perceive to be at risk over the privacy of their data and the potential for non-consented use. Therefore, while developers continue to learn the capabilities of this new technology, the priority for developers should be ensuring the security and privacy of user interactions with the voice assistant. Additionally, service providers should take steps to reassure and educate individuals on the measures in place to ensure data privacy. For example, hardware and software providers such as Google and Amazon have taken recent steps to include *voice printing*, which uniquely identifies the user of the device and stops the voice assistant from detailing personal information to anyone other than the main user. Alleviating such concerns on the individual's part would see further interaction with the technology.

Overcoming the issues of security and privacy concerns, the findings illustrate that the symbolic benefits of the voice assistant motivate its use. Given that the in-home voice assistant is a household item, producers could offer a range of design lead and aesthetically pleasing devices to match the design of the user's home.

Lastly, our findings noted the effect of household size. Therefore, service providers should acknowledge the opportunity to segment communications messages targeted at each group. Households with fewer occupants are more likely to turn to voice assistants for social interactions and even hedonic benefits, this is different from the general motivators for use of the assistant. Thus, voice assistants may serve as a means of overcoming loneliness in a household with fewer occupants.

4. Limitations and future research

The limitations in this research offer opportunities for future research. This research identified the unique social benefits of voice assistants, namely social presence and social attractiveness of the voice enabled technology. Future research could further explore the unique variables of AI powered voice assistants such as the perceived intelligence of the assistant and further examine the demeanour of the assistant on the adoption and use of the technology.

Additionally, this research affirms the importance of utilitarian benefits motivating the continuous use of in-home voice assistants, future research should examine the factors influencing the utilitarian benefits to provide designers with specific practical guidelines.

Furthermore, this study was limited to the Amazon Echo in-home voice assistant. It would be useful to test our model with other in-home voice assistants in order to enhance the generalisability of the findings. Accordingly, through the use of an experiment, future research may be able to manipulate characteristics of the voice assistant such as personality, demeanour, perceived social attractiveness to assess the effects on use of the technology.

Moreover, caution should be noted over our findings regarding household size. We categorised household size by (1) small household and (2) large household, it would be useful for future research to examine this in more detail comparing a variation of household sizes and uncovering the composition dynamics of the household. For example, households comprising of a mix of adults and children, adults only, couples and room-mates. Further exploring the household dynamic would extend our understanding of the differences in use of the technology.

Additionally, this research focused on the voice-based interactions with an individual's voice assistant. We acknowledge that other interactions can occur through the user interface on the echo device itself and through the Alexa mobile application. Future research could consider the influence of non-voice based interaction with a voice assistant on continuous use of the technology.

Lastly, future research should further consider the role of perceived privacy concerns. This research found a dampening moderating role of perceived privacy risks. Thus, researchers should further examine the concerns of users in their interactions with voice assistants. For example, through the use of qualitative interviews researchers may be able to draw out the key concerns as to why individuals are apprehensive over some interactions with voice assistants, in turn providing developers a set of actions for improving security and instilling confidence in the user.

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