Adoption of Smart Voice Assistants Technology among Airbnb Guests: A Revised Self-Efficacy-Based Value Adoption Model (SVAM)

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Highlights

- Perceived functional value, perceived emotional value and perceived privacy risk were the significant determinants for Airbnb guests' intention to adopt SVAs, while the effect of perceived social value was insignificant.

- Self-efficacy directly influenced SVA adoption intention among Airbnb guests and indirectly via the perceived values.

- Our multiple group analysis suggests that self-efficacy on perceived functional value contrasts significantly between everyday users and occasional users.

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Abstract

Smart technology applications in hospitality can leverage user experience values only if they are motivated to adopt the provided technology. This study aimed to understand Airbnb guests' intentions to adopt smart voice assistants (SVAs) like Amazon Alexa or Google Home. Underpinned by social cognitive theory (SCT), a revised self-efficacy-based value adoption model (SVAM) was developed for the study. A survey sample of 255 UK Airbnb guests was analysed using PLS-SEM statistical technique. The results indicate that perceived functional value, perceived emotional value and perceived privacy risk were the significant determinants for Airbnb guests' intention to adopt SVAs, while the effect of perceived social value was insignificant. Self-efficacy directly influenced SVA adoption intention among Airbnb guests and indirectly via the perceived values. Our multiple group analysis suggests that self-efficacy on perceived functional value contrasted significantly between everyday users and occasional users. This study is one of the pioneering empirical studies investigating guests' technology adoption behaviour in the Airbnb context. Specifically, the revised SVAM model advances SCT literature and contributes to understanding smart technology adoption associated with Airbnb guests. Also, this study provides practical implications for Airbnb stakeholders to enhance the Airbnb guest experience value by using Airbnb smart technology applications.

Keywords

Self-efficacy; Smart voice assistant; Airbnb; Perceived value; Privacy risk; Technology adoption

1. Introduction

Airbnb is one of the most successful sharing economy models that has disrupted the hospitality industry. Since its introduction in 2008, Airbnb has seen seven million home listings across 200 countries with a $4.7 billion revenue in 2019 (Helmore, 2019). One of the key differentiating factors of Airbnb lies in engaging communication between the hosts and guests (Jiang et al.,, 2019). This relates to guests' atmospheric feelings or emotions when staying in Airbnb listings and interactions with hosts (Zhang et al., 2020). However, it is important to note that not all guests appreciate atmospheric interactions, and some prefer the serenity of being left alone (Scerri and Presbury, 2020). In this sense, technology becomes an important amenity in Airbnb listings where guests have more options over the type of interactions they wish to engage in (Yu et al., 2020). Concomitantly, the COVID-19 pandemic has forced hospitality providers to offer contactless service to limit the spread of COVID-19 (Jiang and Wen, 2020), where the usefulness of technology has emerged as a prominent alternative to provide safe service interactions. The installation of a smart speaker and voice assistant (SVA) such as Amazon Alexa or Google Home in hospitality and Airbnb accommodation has gained momentum in recent years (Amazon Alexa, 2019). This is witnessed in the UK particulary. According to Mintel (2020), the ownership of standalone voice-controlled speakers such as Amazon Echo and Google Home in the UK reached 29% in 2020, continuously rising from 23% in 2019.

Among other smart technologies, AI and voice control are predicted to have a tremendous impact on the hospitality industry (Salazar, 2018; De Keyser et al., 2019). This is particularly significant for Airbnb where SVA technology enables human-computer interaction such as instantly answering guests' questions, accommodation familiarisation walk-through, and personalised suggestions about local attractions (Mody et al., 2017). Furthermore, the application of SVAs in Airbnb can help guests stay in a private place without a local host serving around (Han and Yang, 2018; Buhalis et al., 2019). In summary, SVAs can enhance Airbnb guests' experienced values in terms of authenticity, localness, community and personalisation, which are unique aspects for Airbnb to outperform traditional hotels (Zhang et al., 2020; Guttentag and Smith, 2017; Birinci et al., 2018).

Smart technology applications in hospitality can leverage user experience values to Airbnb guests if, only if, the guests are motivated to adopt and engage with the provided smart technology (Gretzel et al., 2015). However, little study has investigated the adoption of SVAs among Airbnb Guests. This calls for study about the determinants of SVAs adoption by Airbnb guests.

Extant literature in SVAs adoption in the traditional hotels suggests that in line with the growing population of smart technology applications, customers have increased sophisticated expectations for the technological in-room amenities provided during a stay irrespective of the hotel rating and travel purpose (Bilgihan et al., 2016; Lemy et al., 2019); or use their home as a baseline for evaluating technological offerings in a hotel (Beldona et al., 2018). On the contrary, non-tech savvy guests lack the confidence to use SVAs (Chang, Lu and Yang, 2018). In addition, privacy risks of using smart technologies might hinder guests from technology adoption (Neuhofer et al., 2015; Han and Yang, 2018; Liao et al., 2019). The results of these studies suggest that the SVA adoption intention is likely to vary among customers, which seems to be relevant to their use experience and self-confidence. However, these studies are in the traditional hotel context. It is not clear whether this holds true in the Airbnb context, where the customer expectations and needs may be different from that of the traditional hotels.

Considering the above paradoxical perspectives and significance, this study aims to understand Airbnb guests' intention to adopt SVAs by developing a theoretical model examining the influential factors in Airbnb listings. A critical research gap is the paucity of studies that have been conducted to examine Airbnb guests' intention to adopt SVAs in Airbnb listings. This is in comparison with the plethora of technology adoption behaviour studies that tend to use popular technology adoption models such as technology acceptance models (TAM) (Davis, 1989; Venkatesh and Davis, 2000; Venkatesh and Bala, 2008), uses and gratification theory model (U&GT) (McLean and Osei-Frimpong, 2019), value-based model (VAM) (Kim et al., 2007), and self-efficacy-based value adoption model (SVAM) (Zhu et al., 2017). Although these models have contributed to the understanding of technology adoption behaviour in a variety of research contexts, none of the models can provide a holistic explanation of such a complicated concept as human behaviour. Nevertheless, underpinned by social cognitive theory (SCT), SVAM proposed by Zhu et al. (2017) seems to be the best fit given the context of this study for a number of reasons. First, SVAM considers personal factors (i.e. self-efficacy), which has been found to have a significant effect on adoption behaviour (Carillo, 2010). According to Bandura's (1986) social cognitive theory, self-efficacy (individuals' belief in their own capability) and expected outcomes are the two fundamental determinants of one's behaviour. Self-efficacy is pivotal in understanding technology adoption as it affects human behaviour both directly and indirectly through other classes of determinants such as effort and attention that individuals put into, willing to persevere in the face of obstacles, and outcomes they expect (Bandura, 1999:28). However, there lacks study about the indirect influence of self-efficacy on consumer behaviour, particularly in the Airbnnb context, though self-efficacy's direct effect has been widely studied in information system adoption (e.g. Venkatesh and Bala, 2008; Zhu et al., 2017). Second, SVAM provides a good framework to integrate a range of perceived value factors, including both negatively and positively related to SVA adoption. Thirdly, compared with other models, SVAM has demonstrated a better explanation of power, particularly in a voluntary context, like this research setting (Zhu et al., 2010).

Our study applies a revised SVAM within the Airbnb setting, examining three research questions: (1) What factors influence Airbnb guests' intention to adopt SVAs? (2) How is self-efficacy related to Airbnb guests' intention to adopt SVAs? (3) To what extent does SVA adoption intention differ between different participant groups by their SVAs user experience (e.g. more frequent users versus occasional users)? This study advances original contributions to the body of knowledge in two main areas. Firstly, this study updates the technology adoption literature associated with SVA technology in the Airbnb context. Secondly, our research advances theoretical contributions by developing a revised SVAM model underpinned by SCT. Our results add a significant contribution to the empirical literature, which applied SCT and associated with SVA technology in the Airbnb context. Specifically, this study contributes to understanding the integrative effects of self-efficacy, privacy risks, and (functional, emotional, and social) values on guests' intention to adopt SVA technology.

Following this introduction, the next section reviews the literature and develops a theoretical model and hypotheses for this study. Next, our study explains the methodological approach before the statistical analysis report and results in section four. This is followed by discussing the findings and concluding with theoretical and managerial implications.

2. Literature review

2.1. Defining SVA technology

SVA (technology) is defined as *'internet-connected software which responds to voice commands to provide content and services, interacting with users via digitally-generated voice responses'*

(CDEI, 2019). SVA is currently available as smartphone apps (e.g. Apple Siri and Google Assistant) or standalone devices (e.g. Amazon Echo, Google Home, Apple HomePod). SVA combines technological advances such as speech recognition, natural language processing, semantic web, machine learning, and artificial intelligence (Santos *et al.*, 2018). Recent improvements in the design of SVAs have increased their ability to carry over the context between queries (Barret, 2018) and support multiple languages (Shcwartz, 2019). However, several existing technical limitations still hinders SVAs' regular usage. For example, SVA cannot tell the difference between multiple voices; it often inaccurately understands users' diction and does not provide the desired level of privacy and security (Lopatovska *et al.*, 2018).

Despite the shortcomings, the adoption of in-home SVA technology is on the rise, and almost a quarter of the UK population have become active users (Mintel, 2020). The market leader, Amazon Echo, operated by Alexa, a cloud-based voice service, assists owners with everyday life tasks such as checking the news and weather, making calls and sending messages, music playback, managing the schedule and purchasing items, and controlling network devices (Lopatovska *et al.*, 2018). The key feature of SVAs is the integration with IoT objects, which allows individuals to operate various smart home appliances, including thermostats, locks, doorbells, lights and media systems (Santos *et al.,* 2018).

2.2. Airbnb and SVA usage

With the popularity of the shared economy, Airbnb has enjoyed success and emerged as a key stakeholder with a significant supply of accommodation rooms within the global travel market (Mhlanga, 2020; Ozdenur and Turjer, 2019). Unquestionably, Airbnb has significantly disrupted the traditional tourism and hospitality sector worldwide from various perspectives, particularly via the peer-to-peer platform for short-term rental (Dubois, 2020). Apart from *'economic benefits'*, *'enjoyment'* and *'household benefits'* provided by Airbnb (So et al., 2018), the *'use of entire home'* has gradually become one of the key drives to influence individual's attitudes towards accommodation booking (Guttentag, 2019). Airbnb users are more likely to travel for leisure, visit for pleasure, and not travel alone (Volgger et al., 2018). It is also useful to note that Airbnb has a diverse inventory portfolio including unusual accommodation (e.g., igloos, treehouses) and extremely luxury accommodation (e.g., castles and state homes) to cater to various and flexible customer needs. Hence, the use of SVA can be a key point of contact between the host and guests as a substitute for a physical walk through of the property.

This contactless form of interaction is critical during the COVID19 pandemic where hospitality providers are ensuring physical distancing and improving hygiene to better serve customers using new technology rather than via personal contact in the traditional context (McKinsey, 2020). The use of SVAs such as Alexa guarantee contactless interaction during customers' stay and provide extended services (e.g. background music and concierge) to improve the customer experience. Hence, focusing on the adoption of smart technology among Airbnb guests opens a window to explore innovative approaches as more customers are opting to book entire Airbnb accommodation to avoid sharing or mixing with others in traditional hotels (Bresciani et al., 2021).

2.3. Adopting SVA in hospitality

The application of SVA technology is no longer limited to the consumer market. Various industries have begun to explore the potential benefits of the technology. Some evidence of an early adoption could be found in healthcare, including British NHS (Metrock, 2018; Lake, 2019), business

(Finnegan, 2018), automotive (Wayland, 2019) and hospitality (Ting, 2018) industries. Although the adoption of SVAs is relatively new in the hospitality industry, several large hotel groups have started to integrate SVAs in their hotel operations and service offerings to enhance the customer experience. For example, Wynn Resorts Las Vegas was one of the early adopters who installed Amazon Echo speakers in 4000 hotel rooms in 2016 (Balakrishnan, 2016). The InterContinental Hotels Group partnered with Baidu in 2018 to develop artificial intelligent hotel rooms in China to fully embrace voice control technology for a more convenient and seamless room service experience (IHG, 2018). In 2018, Amazon launched Alexa for Hospitality, a hotel room SVA device to streamline and customise the customer service experience on a single platform (Amazon Alexa, 2019).

However, the Amazon Echo trial by Best Western Hotels and Resorts in 2017 did not go well and reported that most hotel guests disconnected the SVA device because they were concerned about their privacy and did not want Alexa listening to them in the room (Jelski, 2019). Nevertheless, academic research on the impact of SVAs on Airbnb guests' adoption is practically non-existent. Likewise, no comprehensive industry reports on customer satisfaction with SVA from the hotels that launched this service has been published so far.

2.4. Social cognitive theory

Social cognitive theory (SCT) (Bandura, 1986; 2002) proposes that individual factors, social factors and behaviours are interconnected. One's behaviour is determined by their different personal attributes and environmental factors. Meanwhile, individual behaviour also influences their personality and environment. SCT offers a theoretical framework for understanding how observing others, cognition, and the environment interacts to shape human learning behaviour.

Among other SCT elements, self-efficacy has been widely applied in information system adoption studies mostly as a control variable (e.g. Venkatesh and Bala, 2008; Zhu et al., 2017). However, to advance the understanding of SCT, the other underexplored SCT components should be considered (Font et al., 2016) for investigating Airbnb users' adoption of SVA technology application in this study. Further, SCA has been widely applied in education (e.g. Schunk et al., 2020) and health (e.g. Young et al., 2014). To date, there has been limited research applying SCT to the hospitality sector and particularly Airbnb setting in this study. Hence, the conceptual model developed for this study follows the SCT theoretical underpinnings and considers the identified literature gaps in the following section.

2.5. Conceptual model

To develop a model for this study in understanding guests' intention to adopt SVAs in Airbnb listings, we reviewed and critically analysed some of the most popular technology adoption models. Following research suggests that the technology adoption context is equally important for understanding factors influencing the adoption as the technology characteristics themselves do (Carillo, 2010). Our study chose to review those technology adoption models in the hospitality and home-based settings, which are closely related to this research context, i.e. Airbnb accommodation.

Table 1 displays a summary of the most popular technology adoption models and their contributions and limitations. For instance, technology acceptance models (TAM) (Davis, 1989; Venkatesh and Davis, 2000; Venkatesh and Bala, 2008) explain and predict technology and system adoption behaviour mainly from the concepts like perceived 'ease of use' and 'usefulness'. While TAM-based models focus on utility or work purpose, the personal or emotional aspects seem to be largely neglected. The most recent and in-depth study by McLean and Osei-Frimpong (2019) examines the adoption of in-home Alexa through the lens of the use and gratification theory

(U&GT). Compared with the TAM-based model, U&GT seems to explain better users' desire to gratify the range of individuals' needs, including utilitarian, social, hedonic and symbolic. However, their study focused on individuals who have experienced using the technology in the home setting, where privacy and security are of lesser concern in the home context.

Furthermore, the value-based adoption models (VAM) seem to be more appropriate in a voluntary context than TAM, emphasising work or functional purpose (Kim et al., 2007; Zhu, Sangwan, and Lu, 2010). Moreover, in VAM, individuals tend to estimate perceived values, consisting of all benefit and sacrifice factors and decide if the technology is worthwhile. Building on VAM, the self-efficacy-based value acceptance model (SVAM), developed by Zhu et al. (2017), applies SCT to the context of ridesharing applications, where self-efficacy plays a pivotal role influencing cognitive, emotional and social determinants of behaviour in the model. The model demonstrated more effectiveness in explaining the adoption intention than previous similar studies.

Table 1

Summary of key theoretical models applied in the relevant technology adoption research.

Models	References	Contributions	Limitations
TAM-based models	Davis (1989); Venkatesh and Davis (2000); Venkatesh and Bala (2008)	Original TAM proposed by Davis (1989) focuses on two characteristics of a target technology: perceived ease of use (PEOU) and perceived usefulness (PU). TAM2 (Venkatesh and Davis, 2000) explained the determinants of PU construct, such as subjective norm and output quality, while TAM3 (Venkatesh and Bala, 2008) contributed the control variable, most notably, self-efficacy.	TAM and revised TAMs capture adoption mainly for work/functional purpose. Other personal or emotional benefits seem to be neglected.
Uses and Gratification theory (U&GT)	McLean and Osei-Frimpong (2019)	It was claimed that traditional theories, such as TAM, could not fully explain the motivations for adopting AI-based technology in the in-home context. By contrast, U&GT can better explain users' desire to gratify the range of individuals' needs, including utilitarian, social, hedonic and symbolic.	The study focuses on people who have experienced using SVAs and does not consider the non-adopters population.
Value-based model (VAM)	Kim et al. (2007)	Overall, the value-based models seem more appropriate in a voluntary context than TAM, which focuses on work/functional purpose. In VAM, individuals tend to estimate perceived	While VAM has achieved quite a good model performance across several studies,

		value, consisting of all benefit and sacrifice factors and decide if the technology is worthwhile.	SVAM integrating self-efficacy construct into VAM has demonstrated significantly higher explanatory power for adoption intention.
Self-efficacy-based value adoption model (SVAM)	Zhu et al.(2010); Zhu et al.(2017)	In addition to the advantages of VAM, SVAM takes into consideration personal factors, e.g. self-efficacy, which has been found to have a direct effect on adoption behaviour	

As illustrated in Fig. 1, our conceptual model was developed by revising Zhu et al.'s (2017) SVAM. Our study posited the direct relationships between perceived SVA values (measured by functional value, emotional value, and social value) and adoption intention. In contrast, their relationships are mediated by attitude and perceived value (an overall concept) in Zhu et al.'s (2017). This revised model permits a better understanding of the different effects of functional, emotional, and social values on SVA adoption intention. Our study also focused on studying the effects of self-efficacy and perceived values on SVA adoption intention by excluding attitude in this study. The study's exclusion of attitude is consistent with previous SVAM-based studies (e.g. Kim et al., 2007). Further, instead of 'cost' as negative aspects of perceived value in Zhu et al.'s (2017) study, privacy risk is utilised in our model, which is more relevant to guests' perceptions in the Airbnb setting for this study (So et al., 2018).

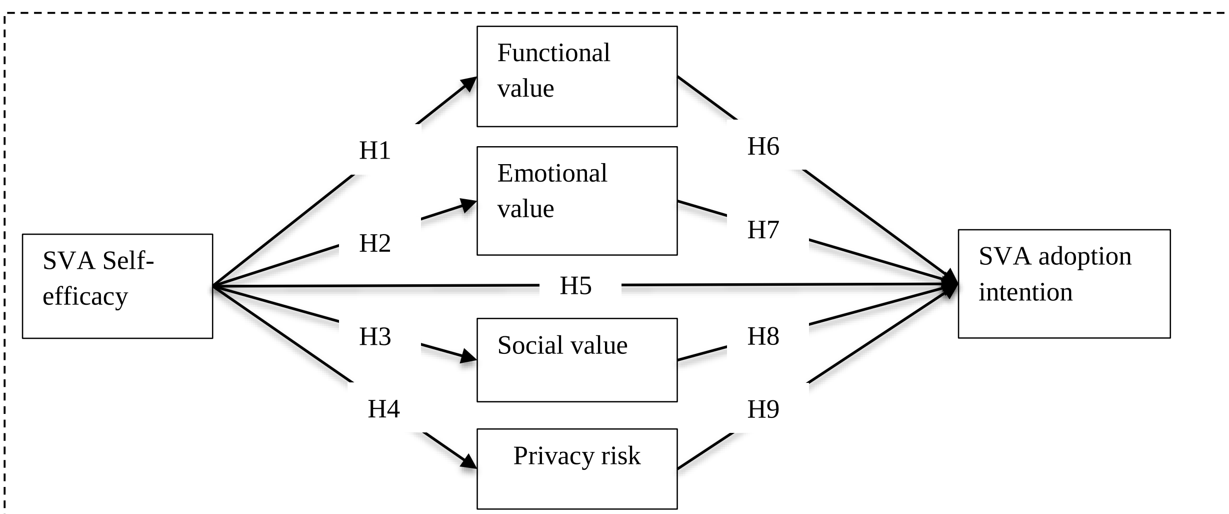

Fig. 1. Conceptual model of guests' SVA adoption in Airbnb.

2.6. Hypotheses development

Our hypotheses are anchored on the theoretical structure of self-efficacy that refers to the extent of an individual's confidence in their capabilities to perform a task or achieve a goal (Bandura, 1986). Unlike more stable personality traits, self-efficacy is situational (Bandura, 1999) and subjective based on a person's self-judgment. Hence, self-efficacy is different from a person's actual skills (Hsu and Chiu, 2004). As a task-specific self-efficacy in this study, SVA self-efficacy refers to the belief that one can successfully perform a set of SVA tasks, such as in-room device control, information search and music playback.

According to SCT theory, self-efficacy influences human behaviour both directly and indirectly via other SCT components such as outcome expectations (Bandura, 1986). Following the study of Zhu et al. (2010), our research employs functional, emotional and social values of SVA usage as expected outcomes of SVA usage. In other words, one has a stronger belief of his or her capability to use SVA. The positive effect of task-specific self-efficacy on functional, emotional and social values has been demonstrated to be significant by Zhu et al. (2010) and Zhu et al. (2017).

Previous research in technology has established that the key functional value in-home SVA provides to the users is convenience and hands-free control (Lopatovska et al., 2019; McLean and Osei-Frimpong, 2019). Additionally, an SVA as an enabler of smart service during a stay in Airbnb simplifies the decision-making process, personalises the experience, and reduce information overload (Kabadayi et al., 2019). Emotional value refers to the degree to which users expect to gain hedonic rewards, such as fun and enjoyment, through the use of SVA (Rauschnabel et al., 2018). Authors have found emotional value from entertaining requests, such as playing music and telling jokes, among the most frequent interactions (Sciuto et al., 2018; Lopatovska et al., 2018;

Ammari et al., 2019). The ability to interact with SVA using natural language creates an unprecedented level of social motives to engage with the technology (Han and Yang, 2018). Studies have found that SVA can provide a sense of companionship while also being an assistant and a source of information and entertainment (Purington et al., 2017). Previous studies have confirmed social value in the context of mobile auctions (Zhu et al., 2010) and ridesharing apps (Zhu et al., 2017).

Airbnb is an innovative business model, representing the sharing economy under the hospitality context has successfully introduced a new lifestyle to individual consumers via technology innovation (Botsman and Rogers, 2010; Guttentag, 2015; Tussyadiah, 2015). While consumers greatly enjoy the benefits brought by the new technology, the related risks gradually merge and challenge business sectors (Yi et al.,2020).

One of the key risks (privacy risk) is defined as a negative association with disclosing performance information of SVA usage, for instance, 'potential loss of control over personal information when your personal information is used without your knowledge or permission' (Featherman and Pavlou, 2003, p.455). Online service platform providers, including Airbnb, naturally request rich and sensitive information from consumers. This sees privacy risk as one of the key factors to evaluate the success of the online service sector (Lutz et al., 2018). Compared with the traditional accommodation service (e.g., staff on duty in a hotel), SVA (e.g., Alexa) is closely located to the customers (in their rooms) and works efficiently to collect consumer data through real-time interaction 24/7. Therefore, it is critical to understand individuals' attitudes towards SVA in a private setting (private rooms) under the context of peer-to-peer accommodation.

Much debate around privacy and security concerns is related to SVA's data collection and use practices as smart speakers continuously listen to a conversation until the wake word (e.g. "Alexa") is detected. Afterwards, the conversation is being recorded and sent for cloud processing. Accordingly, adverse implications may include accidental recording, eavesdropping, unauthorised use of recordings, or unwanted advertising (Lau, Zimmerman and Schaub, 2018; Liao et al., 2019). Past research conducted with smart homeowners has indicated that lack of privacy concerns stems from the perception that users "have nothing to hide" or do not feel personally targeted (Zeng, Mare and Roesner, 2017). The study of Luo et al. (2010) conceptualises that people with a higher level of self-efficacy feel less threatened by the risks associated with the use of technology. The negative relationship between self-efficacy and perceived risk has been confirmed in the B2C e-commerce environment (Kim and Kim, 2005) but disproved in the contexts of mobile banking (Luo et al., 2010) and ridesharing applications (Zhu et al., 2017). Therefore, this study proposes the following hypotheses:

H1. Self-efficacy is positively related to Airbnb guests' perceived functional value of SVA usage.

H2. Self-efficacy is positively related to Airbnb guests' perceived emotional value of SVA usage.

H3. Self-efficacy is positively related to Airbnb guests' perceived social value of SVA usage.

H4. Self-efficacy is positively related to Airbnb guests' perceived privacy risk of SVA usage.

Many studies have investigated the relationships between self-efficacy and behavioural intention of technology-based self-service adoption in various contexts such as hospitality (Oyedele and Simpson, 2007), stock investment (van Beuningen *et al.,* 2009) and ridesharing (Zhu et al., 2017), to name a few. It is important to note that both users and non-users share the perception of engaging with SVA as a trade-off between privacy and convenience and making a conscious decision to adopt or reject the technology (Lau et al., 2018). Similarly, SCT holds that people are more willing to take on tasks they think they can succeed in and avoid those they cannot (Wang et al., 2013). A few empirical studies have supported the idea that self-efficacy positively influences the intention to adopt the technology (Hsu and Chiu, 2004; van Beuningen *et al.*, 2009; Wang *et al*., 2013). Thus, the following hypothesis is proposed:

H5. Self-efficacy is positively related to Airbnb guests' SVA adoption intention.

The VAM literature suggests that perceived technology value positively influences technology adoption behaviour (Kim et al., 2007; Zhu et al., 2017). For instance, the key functional value in-home SVA provides to the users is convenience and hands-free control to complete goal-driven tasks (Lopatovska *et al.*, 2019; McLean and Osei-Frimpong, 2019). Also, an SVA acts as an enabler of smart service during a stay in Airbnb, simplifying decision-making and personalising experience (Kabadayi *et al.*, 2019).

Emotional value refers to the degree to which users expect to gain hedonic rewards such as fun and enjoyment through the use of SVA (Rauschnabel et al., 2018). Although the effect of hedonic benefits on SVA usage is insignificant in the study of McLean and Osei-Frimpong (2019), other studies have found entertaining requests, such as playing music and telling jokes, among the most frequent interactions (Sciuto *et al.*, 2018; Lopatovska *et al.*, 2018; Ammari *et al.*, 2019), which indicates hedonic consumption. Also, Kim et al. (2007) and Zhu et al. (2017) suggest that emotional value positively influences technology adoption behaviour.

The Airbnb platform enables social interactions between guests, hosts and other individuals within local communities (Mody et al., 2017). Such interactions facilitated by a host include welcoming, showing guests around, giving tips on local attractions and spending time together for value to be co-created (Camilleri and Neuhofer, 2017; Johnson and Neuhofer, 2017; So, Oh and Min, 2018). Some studies have also examined community belonging (Möhlmann, 2015) and social appeal (Tussyadiah, 2016; Guttentag et al., 2018; So et al., 2018), among other social values to use Airbnb.

Social relationships with SVAs have been widely investigated in academic literature (Purington et al., 2017; Han and Yang, 2018; Lopatovska and Williams, 2018). Studies have found that SVA can provide a sense of companionship while also being an assistant and a source of information and entertainment (Purington et al., 2017; Han and Yang, 2018). Therefore, SVA in Airbnb accommodation can substitute a host and provide the expected social value to some extent. Porcheron et al.(2017) stress fundamental differences between talking to an SVA and a human caused by technology imperfections. Overall, despite current imperfections of the technology, the studies of McLean and Osei-Frimpong (2019) and Han and Yang (2018) have concluded that SVAs convey substantial social benefits.

Privacy risk coexists with perceived values. Privacy risk has been suggested as the most significant barrier for SVA adoption (Lau et al., 2018; McLean and Osei-Frimpong, 2019). The study of Lau et al. (2018) has also demonstrated that non-users who prioritise privacy concerns over other reasons for non-adoption are explaining their choice by distrust to SVA service provider companies (Amazon, Google and Apple). Conversely, SVA users' positive relationships with service providers have been associated with lower levels of privacy concerns over products (Zeng et al., 2017; Liao et al., 2019). Building upon the above discussion, our study posits the below hypotheses:

H6. The perceived functional value of using SVA is positively related to SVA adoption intention.

H7. The perceived emotional value of using SVA is positively related to SVA adoption intention.

H8. The perceived social value of using SVA is positively related to SVA adoption intention.

H9. The perceived privacy risk of using SVA is negatively related to SVA adoption intention.

3. Methodology

3.1. Measurement

Our theoretical model consists of six constructs: self-efficacy, functional value, emotional value, social value, privacy risk, and adoption intention. Measurement items of the constructs were adapted from the relevant literature. A 5-point Likert scale was used, labelled from *'strongly disagree'* ('1') to *'strongly agree'* ('5'). Four items of self-efficacy (SE) were adopted from Hsu and Chiu (2004). Privacy risk (PR) was measured by four items borrowed from McLean and Osei-Frimpong (2019). Two measurement items of adoption intention (AI) were adapted from Zhu et al. (2010), and three measurement items of emotional value (EV) were borrowed from Zhu et al. (2010). Functional value (FV) was operationalised based on the study of in-home SVA adoption (McLean and Osei-Frimpong, 2019) but also including points from the conceptual study of smart services in the hospitality industry (Kabadayi *et al.*, 2019). Additionally, drawn upon the previous work of Camilleri and Neuhofer (2017) and Johnson and Neuhofer (2017), three items of social value (SV) were developed to capture the perceived social value of SVA technology in comparison with that of an Airbnb host.

3.2. Sampling

The target population has been defined as UK Airbnb guests who have experienced Airbnb stay (at least one stay) and SVAs usage. Two screening questions were used to ensure that only qualified respondents took the survey. The number of UK residents using Airbnb has exceeded 11.1 million by 1 July 2018 (Airbnb, 2018). UK has the second-largest penetration rate of home SVAs after the US (McNair, 2019). The case of Amazon Alexa and Google SVA in Airbnb will be investigated since both SVAs are market leaders in their respective categories. Nevertheless, a relatively small proportion of individuals is qualified for the study, which characterises a hard-to-reach population (Marpsat and Razafindratsima, 2010). Therefore, online non-probability sampling has been used. The participants were recruited via Amazon Mechanical Turk (MTurk), an online platform popular in social science research. The population of MTurk is primarily young, well-educated and IT literate (Paolacci et al., 2010), which fits with the key demographics of Airbnb guests in the UK (Mintel, 2020).

3.3. Data and procedure

A pilot study was conducted online through SurveyMonkey in December 2019 to eliminate potential problems in the questionnaire design at an early stage (Ekinci, 2015), which largely influences the validity and reliability of data collected (Saunders, Lewis and Thornhill, 2019). Eight voluntary respondents consisted of three fellow postgraduate researchers and five local residents who all had Airbnb stay experience in the UK and used IPA either on a mobile device or a smart speaker. It took them 6-7 minutes on average to complete the questionnaire. From the participants' feedback, the questionnaire was revised. For instance, some rewording was made to avoid ambiguity.

Following Hair et al.'s (Hair et al., 2019) suggested sample-to-item ratio, i.e. 1:10, a minimum sample size of 200 was decided based on the number of items (i.e. 20) in a study. We used the MTurk agency service for the main data collection. It lasted two weeks in January 2020. MTurk applied an online (voluntary response) non-probability sampling method, and all eligible MTurk panel users were approached. As a result, a total number of 329 individuals participated in the full launch of the survey. Among them, seven were unaware of SVA technology, and 27 have never stayed in Airbnb. Therefore, these 34 respondents did not pass the survey screening. This resulted in 295 submitted questionnaires, and 40 among them were identified as incomplete ones. Hence, a sample of 255 responses was extracted as valid for further analysis.

For statistical analysis, covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM) are two commonly applied in behavioural sciences. Our study used PLS-SEM analysis due to several reasons. *Firstly*, compared with CB-SEM, which is more restrictive in terms of normal data distribution and acceptable sample size, PLS-SEM is more liberal (Uysal, Schwartz and Sirakaya-Turk, 2016; Hair *et al.*, 2019) and hence preferred in this study. *Secondly*, PLS-SEM is recommended for theory exploration, whereas CB-SEM for theory confirmation (Hair *et al.*, 2019). The conceptual framework used in the study was developed by Zhu et al. (2017). Hence, a confirmatory approach to testing theory does not apply (Uysal et al., 2016). *Further*, PLS-SEM is preferable for the complex models by the number of constructs, indicators and relationships (Hair *et al.*, 2019), which also applies to this study.

The demographic characteristics of the total 255 participants and their experience using SVA technology and Airbnb accommodation are demonstrated in Table 2. The sample consists of a higher proportion of males (63.1%) over females (34.1%). Our sample's disproportionate gender characteristics are consistent with the demographic structure in the UK MTurk (Difallah et al., 2018). The majority of the respondents were 25 to 34 years old (50.6%), while 18 to 24 and 35 to 44 age groups each amounts to approximately 20 per cent of the total sample, and the 45 and above age groups accounted for less than 10 per cent. The majority of the participants (89.4%) have attained a higher education (i.e. college or above degrees), which is in line with Paolacci and Chandler's (2014) study of MTurk population characteristics.

Table 2

Descriptive statistics of the respondents.

Indicator	**Category**	**Frequency**	**Per cent**
Gender	Female	87	34.1
	Male	161	63.1
	Prefer not to say	7	2.8
Age	18 to 24	47	18.4
	25 to 34	129	50.6
	35 to 44	54	21.2
	45 to 54	19	7.4
	55 and above	6	2.4
Education	High school or less	27	10.6
	College or university	157	61.6
	Advanced degree	71	27.8
SVA use experience	Everyday user	125	49
	Occasional user	130	51
SVA current usage*	Amazon Alexa	133	52.2
	Google Assistant	119	46.7
	Apple Siri	91	35.6
Airbnb stays	Once	43	16.9
	2-5 times	143	56.1
	6 and more times	69	27.0

Note. * This is a multiple-choice question to the indicator, SVA current usage. Some use more than one SVA, and therefore, the sum of the frequency is more than the sample size (n= 255).

Regarding the user experience with SVAs, 49 per cent of respondents reported everyday usage, while 51 per cent consider themselves occasional users. Our data show that the number of Alexa users (52.2%) is slightly higher than Google Assistant (46.7%). Some participants reported using more than one SVA, with Amazon Alexa and Google Assistant being the most popular combination.

4. Analysis and Results

4.1. Measurement model analysis

We first performed the measurement model analysis, including factor loadings, internal consistency, convergent and discriminant validity. As seen in Table 3, our factor loadings for the measurement models exceed the recommended threshold value of 0.7, indicating acceptable measurement reliability (Hair *et al.*, 2019).

Table 3

Loadings, means and standard deviations (SD).

Construct (reference)	Questionnaire items	Mean/SD	Loadings
Self-efficacy (SE) (Hsu and Chiu, 2004)	SE1: I believe I have the ability to use a smart voice assistant	4.176/.952	0.879
	SE2: I am confident that I am able to control in-room devices via a smart voice assistant	3.973/.955	0.857
	SE3: I am confident that I am able to find information about local restaurants using a smart voice assistant	3.918/1.051	0.867
	SE4: I am confident that I am able to play music using a smart voice assistant	4.204/1.005	0.897
Functional value (FV) (McLean and Osei-Frimpong, 2019; Kabadayi et al., 2019)	FV1: Completing tasks with a smart voice assistant can be time-saving during my stay in Airbnb	3.706/1.023	0.825
	FV2: Completing tasks with a smart voice assistant can be convenient during my stay in Airbnb	3.529/1.098	0.818
	FV3: Using a smart voice assistant can personalise my stay in Airbnb	3.686/.984	0.842
	FV4: Overall, a smart voice assistant can be useful during my stay in Airbnb	3.686/.964	0.867
Emotional value (EV) (Zhu et al., 2010)	EV1: Using a smart voice assistant may be enjoyable during my stay in Airbnb	3.639/1.046	0.882
	EV2: Using a smart voice assistant may be fun during my stay in Airbnb	3.533/1.102	0.909
	EV3: Using a smart voice assistant may be exciting during my stay at Airbnb	3.651/1.102	0.882
Social value (SV) (Camilleri and Neuhofer, 2017; Johnson and Neuhofer, 2017)	SV1: A smart voice assistant could help me to learn about home amenities when my host is not around	3.094/1.211	0.735
	SV2: A smart voice assistant could help me to learn about the neighbourhood when my host is not around	3.780/1.058	0.842
	SV3: I believe a smart voice assistant might effectively replace interactions with my host during a stay in Airbnb	3.686/1.042	0.842

Privacy risk (PR) (McLean and Osei-Frimpong, 2019)	PR1: I have my doubts over the confidentiality of my interactions with a smart voice assistant	3.373/1.242	0.850
	PR2: I am concerned that a smart voice assistant collects too much information about me	3.286/1.195	0.816
	PR3: I am concerned to share my information with a smart voice assistant installed in Airbnb accommodation	3.376/1.214	0.851
	PR4: I am concerned that the host may be able to access my personal information if I use a smart voice assistant during my stay	3.267/1.198	0.851
Adoption intention (AI) (Zhu et al., 2010)	AI1: Assuming I have access to a smart voice assistant next time I stay in Airbnb, I am likely to use it	3.561/1.153	0.926
	AI2: In the future, I intend to book Airbnb accommodation featuring a smart voice assistant	3.278/1.072	0.885

Next, our measurement model analysis used Cronbach's alpha (CA) and composite reliability (CR) coefficients to examine internal consistency. Based on Hair et al.'s (2019) guidelines, both parameters should exceed a minimum of 0.7 and remain below 0.95. As shown in Table 4, the proposed model for the present study meets the criteria.

Construct validity consists of convergent validity and discriminant validity. The convergent validity of a construct is measured by the average variance extracted (AVE) and the suggested threshold value to be above 0.5 (Hair et al., 2019). As seen in Table 4, our results revealed AVE values, ranging from 0.653 to 0.821, achieving an acceptable convergent validity level. Discriminant validity was examined via cross-loading indicators on unrelated constructs and the Fornell-Larcker criterion (Hair *et al.,* 2019). Discriminant validity criteria are met when factor loadings are the highest for their designated constructs (Appendix 1). Furthermore, our Fornell-Larcker criterion in Table 4 shows that AVE's square root on the diagonal is higher than its corresponding correlations with other latent variables, suggesting good discriminant validity (Hair et al., 2019).

Table 4

Construct internal consistency, convergent and discriminant validity.

	CR	CA	AVE	1	2	3	4	5	6
1 Adoption intention	0.929	0.898	0.766	0.906					
2 Emotional value	0.904	0.859	0.702	0.805	0.891				
3 Functional value	0.920	0.870	0.794	0.735	0.803	0.838			
4 Privacy risk	0.849	0.733	0.653	-0.205	-0.072	-0.018	0.842		
5 Self-efficacy	0.907	0.865	0.709	0.327	0.499	0.585	0.229	0.875	
6 Social value	0.902	0.784	0.821	0.629	0.700	0.748	0.009	0.487	0.808

4.2. Structural model analysis

We conducted Algorithm test and Bootstrapping test with 5000 subsamples. Our results, showing in Table 5, suggest that except for H8, eight of the nine proposed hypotheses were supported. Self-efficacy was a strong predictor of perceived SVAs values, including functional value ($\beta = 0.585$; $t = 11.686$), emotional value ($\beta = 0.499$; $t = 8.722$), and social values ($\beta = 0.486$; $t = 8.056$). Self-efficacy was also positively related to privacy risk though the effect size ($\beta = 0.229$; $t = 3.155$) was much smaller than the perceived values. Also, the direct effect of self-efficiency on SVA adoption intention was statistically significant. Hence, H1 to H5 are supported. Perceived emotional value was the strongest determinant of SVA adoption intention ($\beta = 0.576$; $t = 7.747$). Perceived functional value ($\beta = 0.295$; $t = 3.905$), together with perceived emotional value, positively influence SVA adoption intention. In contrast, privacy risk ($\beta = -0.126$; $t = 3.272$) had a negative effect on SVA adoption intention., Hence, H6, H7, and H9 are supported.

Table 5

Test results of the hypotheses and the model.

Paths	Coefficients	T Statistics	Result
H1: SE → FV	0.585***	11.686	Supported
H2: SE → EV	0.499***	8.722	Supported

H3: SE → SV	0.486***	8.056	Supported
H4: SE → PR	0.229**	3.155	Supported
H5: SE → AI	-0.141**	2.848	Supported
H6: FV → AI	0.295***	3.905	Supported
H7: EV → AI	0.576***	7.747	Supported
H8: SV → AI	0.075	1.373	rejected
H9: PR → AI	-0.126**	3.272	Supported

Note. ***ρ<0.001, **ρ<0.01, *ρ<0.05 (two-tailed).

Figure 2 illustrates the graphical results of the analysis. As per R squares, our model reported a strong predictive power of over 70 per cent of the variance in adoption intention (Hair *et al.*, 2019).

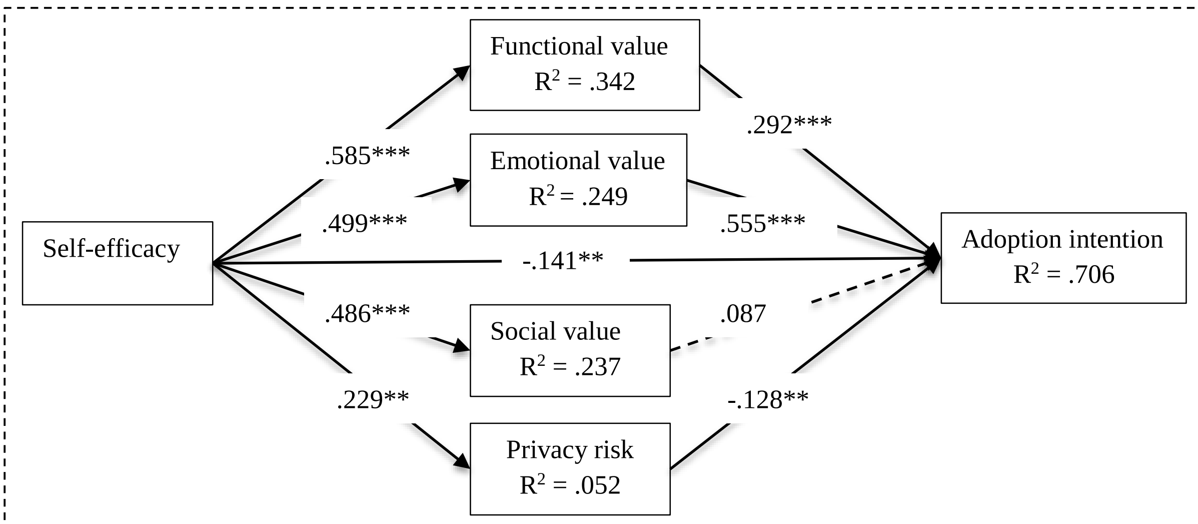

Fig. 2. PLS results of the structural model analysis.

Note. The dotted line represents an insignificant path. ***ρ<0.001, **ρ<0.01, *ρ<0.05 (two-tailed).

4.3. Multi-group analysis

Given that SCT postulates that technology adoption behaviour differs between different groups of people based on their individuals' use experience (Bandura,1986; Carillo, 2010), our study conducted a multi-group analysis (MGA). MGA allows testing if participant groups have significant differences in the model. Our study assessed the differences between categorical groups by SVA use experience: G1 (Everyday user; n=105) vs G2 (Occasional user; n=115).

Comparing everyday and occasional SVA user groups (Table 6) indicates that the effect of self-efficacy on functional value differs significantly ($\Delta\beta = 0.252$; $\rho = 0.011$) between the two groups. Everyday users (G1) have stronger perceived functional values than occasional users (G2). Moreover, everyday users and occasional users differ in coefficients (columns 2&3) and the corresponding statistical significances (columns 4&5). The effects of functional value, privacy risk, and self-efficacy on adoption intention, and the effect of self-efficacy on privacy risk, are all significant in G2 but insignificant in G1.

Table 6

PLS-MGA results (Everyday users G1 versus Occasional users G2).

	Coefficients (β)		t-Values		Δβ	p-Values
	G1	G2	G1	G2	PLS-MGA (G1 vs G2)	
Emotional value -> Adoption intention	0.616***	0.560***	4.491	6.082	0.056	0.363
Functional value -> Adoption intention	0.128	0.262**	0.734	2.600	0.134	0.735
Privacy risk -> Adoption intention	-0.079	-0.167*	1.218	2.532	0.088	0.168
Self-efficacy -> Adoption intention	-0.086	-0.195**	0.745	3.118	0.109	0.202
Self-efficacy -> Emotional value	0.603***	0.412***	6.281	4.832	0.191	0.075
Self-efficacy -> Functional value	0.709***	0.457***	10.939	5.330	0.252*	0.011
Self-efficacy -> Privacy risk	0.218	0.295**	0.970	2.942	0.077	0.573
Self-efficacy -> Social value	0.559***	0.377***	6.011	3.527	0.182	0.102
Social value -> Adoption intention	0.193	0.105	1.711	1.412	0.088	0.256

Note. $^{***}\rho<0.001$, $^{**}\rho<0.01$, $^{*}\rho<0.05$ (two-tailed).

5. Discussion and Conclusion

This study aims to understand guests' intentions to adopt SVA technology in Airbnb accommodation. Our evidence suggests that SVA self-efficacy is a strong predictor of perceived functional, emotional and social values (H1, H2 and H3). The result implies that people with greater confidence to perform SVA tasks are more likely to perceive SVA values. This finding is consistent with previous studies [Zhu et al. (2010) and Zhu et al. (2017)]. Concomitantly, MGA establishes that the more user experiences a person has with SVAs, the stronger the relationship between self-efficacy and the perceived functional value of SVA in Airbnb. This result is in line with the previous study in Lau et al. (2018).

SVA Self-efficacy is found to be positively related to perceived privacy risk (H4). This suggests that higher self-efficacy is more likely to cause perceived privacy risk of using SVA. One possible explanation is the increased awareness or knowledge of privacy risks in using SVAs in Airbnb accommodation. Our finding is different from the studies of Luo *et al.* (2010) and Zhu et al. (2017), who found no significant effect of self-efficacy on perceived privacy risk.

Overall, the results regarding the direct effect of self-efficacy on technology adoption in the literature are inconsistent. We found that SVA self-efficacy is positively related to SAV adoption intention (H5) in the Airbnb setting. Similar to our finding, previous research indicated that self-efficacy has a positive impact on intention to adopt self-checkout SST (Wang et al., 2013), hotel SST (Oyedele and Simpson, 2007) and technology-based self-service in the context of online stock investment (van Beuningen *et al.,* 2009). However, Liang and Lu (2013) and Zhu et al. (2017) provided no support for this relationship in studies of a tax filing system and a ridesharing application, respectively.

Our findings revealed both perceived functional and emotional values as strong predictors of SVA adoption intention during a stay in Airbnb (H6 and H7), whereas perceived social value attributes a smaller and insignificant contribution (H8). These results match those observed in earlier studies in various contexts (Kim et al., 2007; Zhu et al., 2017). However, our findings are inconsistent with McLean and Osei-Frimpong (2019). They found functional and social benefits to influence usage of in-home SVAs, while the effect of hedonic benefits is insignificant. The inconsistent results might be related to the different settings between in-home and Airbnb, where people have a different mindset regarding expectations or goals in using SVAs.

5.1. Theoretical implications

Our study contributes to existing knowledge by developing the revised SVAM to investigate guests' intentions to adopt SVA technology in Airbnb accommodation in four key theoretical implications. First, self-efficacy was found to affect SVA adoption intention directly and indirectly via perceived SVA values (functional, emotional and social) and perceived privacy risk. These findings are in line with the study by Zhu et al. (2017). Therefore, this study updates the SCT empirical evaluation, which was previously popular in education (e.g. Schunk et al., 2020) and health (e.g. Young et al., 014), and we further support the SVAM technology adoption model in an underexplored hospitality sector and the Airbnb setting in particular in this study.

Second, unlike SVAM proposed by Zhu et al. (2017), our model provides direct relationships between three dimensions of perceived value and adoption intention. This enables us to distinguish the different effects of functional, emotional and social values on technology adoption behaviour. The findings demonstrated the complex multi-dimensional nature of perceived value. The perceived emotional value was the strongest determinant in the Airbnb setting, with a much larger effect size than the perceived functional value. In contrast, the effect of perceived social value seemed insignificant. The results suggest that people valued different aspects of SVAs: functional, emotional and social; the importance of the different values perhaps depends on other scenarios such as various research contexts and individual differences (Ham et al., 2019). The concept of overall value in the previous studies does not help understand the insights. Our proposed SVAM enables us to see different values among people and their influence, particularly in the Airbnb setting.

Third, the negative value of SVA was represented in this study by a much-debated aspect of personal data privacy risk. In line with Lau et al. (2018) and McLean and Osei-Frimpong (2019), our evidence suggests that privacy risk was a major barrier in SVA adoption. However, the risk was seemingly outweighed by the benefits mentioned above. This means despite significant obstacles such as privacy concerns, self-confident individuals still adopted the SVA technology due to its perceived values in Airbnb accommodation. Moreover, MGA indicates that privacy risk negatively affected the SVA adoption intention for the occasional users' group. However, the effect was insignificant for the everyday users' group, suggesting that more user experience might reduce privacy concerns against the adoption intention.

Finally, MGA indicates that the more SVAs use experiences a person had with, the stronger the relationship between self-efficacy and perceived functional value of SVA in Airbnb. This result suggests that user experience (e.g. everyday users versus occasional users) and self-efficacy interactively enhanced perceived SVA functional value. This is in line with the SCT theoretical underpinning in terms of the indirect effect of self-efficacy on adoption behaviour.

5.2. Managerial implications

This study pertains to the emerging technology applications in Airbnb, which are assumed to enhance the guest experiences. Overall, the findings demonstrate that SVA technology might be a valuable asset in Airbnb homes and create many business opportunities for different stakeholders. The present study provides practical recommendations to the stakeholders involved in the service delivery process, such as Airbnb hosts, property management companies, Airbnb service itself and software developers.

First, Airbnb hosts need to reinforce the functionality of SVA during the stay of the Airbnb guests as the perceived functional values were a strong predictor of the SVA adoption intention. One effect approach is to for Airbnb hosts to provide sufficient information about the SVA in use before the guests' arrival in written, audio and video formats to meet the needs of different guests. Second, Airbnb hosts could be more innovative in creating and strengthening the emotional attachment with guests using the available SVA in their guest houses. This is important as emotional values were a strong predictor of guests' SVA adoption intention. Airbnb hosts can personalise their record greetings and messages to their guests instead of using the SAV mono-tone function from the SAV to establish a close emotional bond between the hosts and guests. This would also reinforce the distinctive nature of Airbnb accommodation comparing to hotels.

Third, software and smart technology equipment developers should consider designing specific techniques or "skills" in the SVA to improve the Airbnb stay experience made available to consumers as perceived value was the key to adoption. For example, software developers could include smart technology to provide recommendations about local tourist attractions and answering questions about the accommodation facilities. These features could use the input from hosts and integrated third-party services such as restaurant booking platforms. Moreover, developers should focus on the improvement of consistency and accuracy of voice recognition and requests processing. If guests do not feel confident in their abilities to control a smart speaker device, they will not associate it with benefits, such as convenience or fun. Current technological imperfections of SVAs like understanding the accent might contribute to low self-efficacy and thus prevent wider adoption.

Next, the property management company and wider Airbnb service agency need to be mindful that simply installing a smart speaker itself does not directly translate into an ultimate competitive advantage of an Airbnb listing or a reason that guests will pay the price premium, contrary to some practitioners' opinions (August Home, 2016). In other words, Airbnb service should not simply install SVA technology for the sake of service innovation. However, smart service experience in Airbnb, enabled by SVAs with specific "skills" and co-created by guests and a host, probably will. Therefore, chasing a technology trend will be an ineffective strategy or financial investment. Instead, Airbnb services and companies that manage vacation rental listings should adopt the experience value mindset (Pine and Gilmore, 2011). This could maximise the value for all stakeholders involved.

Finally, people's privacy risk, which caused reluctance to adopt SVA technology, should not be ignored. Zeng et al. (2017) found that security and privacy significantly impact trust towards Airbnb. Although a host has a primary role as a service provider and deals with guests' requests at their discretion, Airbnb, as the parent company, could provide hosts with guidelines regarding the use of smart technologies in their listings to protect brand reputation. Consequently, the reduced privacy risk can encourage more adoption of SVA by the guests, especially for those who are conscious about their privacy.

5.3. Limitations and future research

The limitations of this study need to be acknowledged. The study deliberately restricted the demographic profile to match a typical audience of in-home smart speaker users and Airbnb users. Therefore, the findings may not be generalisable beyond the young, educated and tech-savvy population.

This study presented an avenue for future research of applying smart technology in other hospitality and hotel contexts. Some results from comparing the different groups of consumers within the sample were not fully explained in the current study. For example, the findings showed significant variation in the role of SVA self-efficacy to the perceived functional value depending on the user experience. In contrast, use experience did not make a difference to other paths. It would be interesting to understand these observations better.

Taking a qualitative approach in subsequent studies in this field could help develop an in-depth understanding of consumers' attitudes towards SVA from guests' and hosts' perspectives. Another possible area of future research would be to investigate the role of SVA in traditional hotels as the number of hotels considering in-room smart speakers service for their guests will continue to increase. While the industry has already reported mixed results from in-room SVA test launches, obtaining an academic perspective might help develop a better understanding of the phenomenon and possibly provide managers with new insights.

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Appendix 1. Cross-loadings

Item	Adoption intention	Emotional value	Functional value	Privacy risk	Self-efficacy	Social value
AI1	0.926	0.782	0.734	-0.227	0.366	0.609
AI2	0.885	0.667	0.584	-0.135	0.213	0.525
EV1	0.720	0.882	0.781	-0.050	0.527	0.667
EV2	0.724	0.909	0.683	-0.063	0.388	0.600
EV3	0.705	0.882	0.676	-0.080	0.410	0.599
FV1	0.690	0.727	0.825	-0.063	0.484	0.635
FV2	0.561	0.625	0.818	-0.004	0.446	0.618
FV3	0.565	0.629	0.842	0.017	0.462	0.618
FV4	0.632	0.699	0.867	-0.003	0.558	0.635
PR1	-0.152	-0.054	0.023	0.850	0.269	0.032
PR2	-0.085	0.015	0.064	0.816	0.181	0.099
PR3	-0.129	-0.008	0.030	0.851	0.220	0.039
PR4	-0.300	-0.172	-0.155	0.851	0.091	-0.114
SE1	0.219	0.422	0.471	0.279	0.879	0.399
SE2	0.278	0.429	0.514	0.162	0.857	0.428
SE3	0.308	0.424	0.530	0.141	0.867	0.434
SE4	0.334	0.469	0.529	0.222	0.897	0.441
SV1	0.577	0.539	0.549	-0.045	0.193	0.735
SV2	0.457	0.589	0.670	0.054	0.561	0.842
SV3	0.508	0.568	0.587	0.004	0.391	0.842