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EMPIRICAL ARTICLE

Perceived value of AI-based recommendations service: the case of voice assistants

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Abstract

The application of artificial intelligence in services is continuously spreading. In particular, one of the most important recent trends is the development of virtual assistants, more particularly; voice assistants, which provide consumers with various services (e.g. information, music) and with product and service recommendations based on their preferences. There is a need to understand how valuable these recommendations are for consumers. This study contributes to the emerging body of research into consumers' use of the recommendations that voice assistants make in three key ways: (1) by analysing the roles of the benefits (i.e. convenience, compatibility, personalisation) they derive and costs they expend (i.e. cognitive effort, intrusiveness) in the value creation process related to voice assistants' recommendations; (2) by evaluating the effect of social presence (the key voice assistant feature) on perceived value of voice assistants' recommendations, through the benefits and costs associated with voice assistants and (3) by determining how the perceived value of voice assistants' recommendations affects consumer engagement. An online survey was used to collect data. Partial least squares structural equation modelling (PLS-SEM) was employed to analyse the conceptual model. The core findings of the study are as follows. First, social presence enhances the benefits (especially personalisation) and reduces the costs (except for cognitive effort) associated with voice assistants. Second, personalisation was shown to be the strongest determinant of the perceived value of voice assistants' recommendations, but their intrusiveness is a potential inhibitor in the way of increasing their value. Third, a positive relationship was observed between the perceived value of voice assistants' recommendations and consumer engagement with the assistants.

Keywords Social presence · Voice assistant · Recommendations · AI-based services · Virtual assistant · Smart speaker · Perceived value · Engagement · Benefits · Costs

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1 Introduction

In recent times, continuous increases have been seen in the application of automated technologies and artificial intelligence (AI) in services (Flavián and Casaló 2021), probably due to the economic (e.g. increase in firms' efficiency) and social (e.g. healthcare) value they provide. For instance, in the healthcare sector, automated devices are used to assist in operations, take care of elderly patients and manage drug therapies (Hamet and Tremblay 2017). In the frontline of hospitality services, hotels can completely replace traditional forms of customer–employee interactions using AI-robot concierges and in-room virtual assistants to answer customers' queries during their stays (Belanche et al. 2020). AI-based technologies are already being effectively used in the public sphere, for example, in the criminal justice field they are employed: in predictive policing (i.e. algorithms calculate the degree of risk of recidivism and victimisation); to carry out facial recognition tasks (i.e. to automatically identify/authenticate people by matching facial features in two or more digital images) and as digital interrogators (Whitford et al. 2020).

One of the main AI-based applications used in services are voice assistants (VAs): VAs help their users accomplish a variety of tasks [e.g. playing music; making/receiving calls (Chattaraman et al. 2019)]. In addition, VAs can be effectively used to deliver value-added service recommendations (Rhee and Choi 2020). It has been reported that 72% of Google users consult their phones' VAs daily and 52% of this 72% use them to access product and brand recommendations (Georgiev 2022). The way VAs give recommendations differs in important regards from how other agents operate (e.g. consumer online reviews, Chatbots). VAs understand the user's oral commands and needs and respond quickly and accurately (Whang and Im 2021), as well as create value for consumers by saving time and give personalised information, which may subsequently affect their decision-making processes (Rhee and Choi 2020).

Prior research into VAs has been limited mostly to existing general technology adoption frameworks, such as the technology acceptance model (TAM; Davis 1989; Balakrishnan et al. 2021) and the unified theory of acceptance and use of technology (UTAUT; Venkatesh and Davis 2000; Vimalkumar et al. 2021). Hence, research into VAs needs to look beyond the traditional adoption models. More specifically, in the search for added value. There have been calls for researchers to identify key elements, for example VAs that might be incorporated into AI devices (Flavián and Casaló 2021; Belanche et al. 2020). In this respect, recent studies have analysed the value that VAs add, both in general (e.g. Park et al. 2018) and in specific contexts (e.g. hospitality, Loureiro et al. 2021; voice commerce, Rzepka et al. 2020; smart home devices; Benlian et al. 2020). The present study contributes to the emerging, but still limited, body of research examining consumers' use of VAs' recommendations, by addressing three important issues.

First, we analyse the main drivers that increase the perceived value of VAs' recommendations and the barriers that stand in their way. Consumer perceived value is the basis for all marketing decisions: it is a vital construct that has helped scholars decipher consumer behaviours over the past three decades (Zeithaml et al. 2020). Lin and Lu (2015) showed that perceived value is a complex and context-specific phenomenon, which is based on the difference between what the customer gets (benefits) and what (s)he gives (costs). According to cost–benefit framework (e.g. Kleijnen et al. 2007), users consider the costs they will incur and the benefits they will derive from a technology (Hernandez-Ortega and Ferreira 2021) in order to assess the overall value that can affect their behavioural intentions (Lin and Lu 2015). Specifically, amongst the specific highlighted benefits that VA provide are the convenience of communicating via voice input/output and their hands-free functionality (Qiu and Benbasat 2009); their compatibility (how congruent an innovation is with users' values and prior experiences) and personalisation that identifies consumers' preferences from consumer's previous purchases (Mishra et al. 2022). However, previous research has also highlighted the dark side of VAs, such as the cognitive effort required to operate them, and their intrusiveness (McLean et al. 2021), which can undermine consumers' perceptions of their services' value.

Second, we address social presence; in particular, to provide a comprehensive understanding of perceived value in the context of VAs' recommendations. Social presence, the most prominently cited feature of VAs, is the subjective capacity of a technology to make its users believe their interlocutor is psychologically present (Chattaraman et al. 2019). Van Doorn et al. (2017) distinguished between human social presence and automated social presence, that is, the presence evoked by a human's interaction with a technology that engages him/her socially. Social presence is gaining an importance, as companies increasingly replace human service personnel with automated service robots (Verhagen et al. 2014) and because it has been shown to be a crucial antecedent of several key service and customer outcomes (Van Doorn et al. 2017).

Third, this study examines how this perceived value influences consumers' VA-related behaviours. Specifically, we analyse whether the perceived value of VAs' recommendations develop consumers' engagement with VAs. The reciprocity principle (Schmidtz 2006) holds that when one party benefits from relating, or interacting, with another party, it is, at least, a good thing and perhaps a moral obligation, for the beneficiary to return some of that benefit to the other party. From that start point, it is proposed that users become engaged with their VAs to reciprocate the value they derive from the recommendations made by these devices. It has been acknowledged in the previous literature that consumer perceived value is the main antecedent of consumer engagement (e.g. Brodie et al. 2011). In the present study, therefore, we intend to confirm that engagement is a consequence of the perceived value that consumers derive from VAs' recommendations. Specifically, we focus on the behavioural dimension of engagement, that is, the "*level of energy, effort and/or time spent on a brand, in particular interactions*" (Hollebeek 2011, p. 569), which includes proactive behaviours, in particular, eWOM-related behaviours (i.e. spreading eWOM (Brodie et al. 2011), eWOM adoption (Phua et al. 2018)] and continued use (Pal et al. 2021). Consequently, taking into account that behavioural intentions have been shown to translate into actual behaviours (e.g. Venkatesh and Davis

2000), consumer engagement is measured in the present study by the following three behavioural intentions: (1) intention to recommend the VA; (2) intention to follow the recommendation of the VA and (3) continuance intention to use the VA.

Based on the cost–benefit paradigm (e.g. Kleijnen et al. 2007), social presence (e.g. Van Doorn et al. 2017) and engagement (e.g. Hollebeek 2011), the present study develops a research model (see Fig. 1) that investigates the main drivers and barriers of the perceived value of a VAs' recommendations. On the one hand, we propose that social presence is the main antecedent of the benefits (convenience, compatibility and personalisation) derived from, and costs (cognitive effort and intrusiveness) incurred by, using VAs and that these, in turn, exert a direct influence on consumers' perceptions of the value of VAs' recommendations. On the other hand, we examine whether the value generated leads to consumer engagement with the VA, in terms of intention to (1) recommend the VA; (2) follow the VA recommendation and (3) continue to use the VA.

From a practical perspective, this research can assist service providers and VA developers to understand how the technologies should be designed to enhance the perceived value of their recommendations and, subsequently, to foster higher consumer–VA engagement. Specifically, in the VA context, to increase perceived value and consumer–AI engagement, it is very important that social presence and personalisation are maximised and that intrusiveness is minimised.

2 Conceptual background

2.1 Perceived value

A fundamental assumption in consumer behavioural research is that value maximisation (Zeithaml et al. 2020) is a key underlying explanation of the individuals' choices. Prospect theory (Kahneman and Tversky 1979) describes the value as the perceived gain or loss compared to a baseline. It posits that individuals choose to

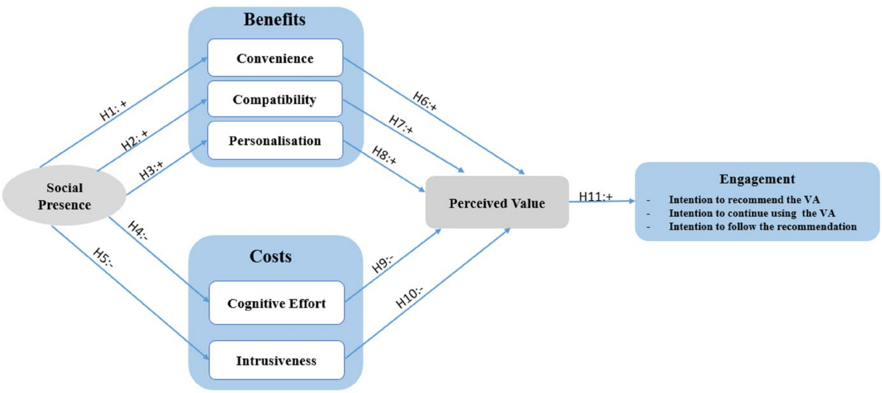

Fig. 1 Research model

conduct behaviours that result in the biggest payouts. In the context of products, perceived value has been described as a compromise between their "*give*" and "*get*" components. Zeithaml (1988) argued that perceived value is the consumer's overall evaluation of a product's usefulness based on his/her views of what (s)he receives and what (s)he provides. From the standpoint of consumer choice, people assess the worth of a choice object by weighing all its advantages and costs (Kahneman and Tversky 1979; Zeithaml 1988). Thus, in the present study perceived value is defined as the consumer's perception of the trade-off between the costs and the benefits (s)he receives from his/her VA. Amongst other benefits, VAs may create value by providing personalised information and targeted recommendations, based on data (i.e. present/past choices, purchases, needs) earlier provided by the consumer, using algorithms and data processing analytics tools (Huang 2018). In addition, as VAs are hands-free devices, they can help their users make quicker decisions and save time and effort (Rhee and Choi 2020). The following section presents the main benefits and costs associated with the VAs.

2.2 Benefits and costs

In the present study the cost–benefit paradigm (Kleijnen et al. 2007) is used as the basis from which to identify the antecedents of the perceived value of VAs' recommendations. Systematic research has suggested that convenience and compatibility are amongst the main benefits of innovative technologies. For example, Tan and Liao (2021) found that convenience is amongst the main benefits consumers derive from online services. Convenience, in this context, relates to consumers' perceptions of the time and effort they expend when using a technology, recognising that technologies can efficiently undertake time-consuming, routine tasks (Ukpabi and Karjaluoto 2017). Several studies explored time and effort saving (Berry et al. 2002) as aspects of convenience in online context. Similarly, in mobile services, it has been shown convenience directly and positively influences perceived value (Lin and Lu 2015). Second, task technology fit theory proposes that a technology's compatibility with its users' beliefs and needs is an important component of perceived value (Goodhue and Thompson 1995). Compatibility has been defined as the degree to which consumers perceive innovations as consistent with their needs, values, past experiences and routines (Goodhue and Thompson 1995). Research into mobile services has shown that compatibility is an antecedent of perceived value (Lin and Lu 2015). Similarly, research into smart speakers (Pal et al. 2021) has found that compatibility is the greatest benefit derived from technology adoption. In the present study, to convenience and compatibility, we add personalisation as a third benefit derived from VAs. Personalisation, in the new media communication context, relates to the extent to which technologies facilitate interpersonal communications and interactions based on their understanding of consumers' personal information and preferences (Rhee and Choi 2020). The findings of communication-based research suggest that personalised communications attract more of the recipient's attention, and are perceived as more beneficial for both the transmitter and the recipient, than are non-personalised communications (Komiak and Benbasat 2006). In the social media context, it has been argued that personalised recommendations enhance the consumers' perceptions of the value (s)he derives from platforms. In the same vein, Rhee and Choi (2020) and Pal et al. (2021) found that personalisation is the main benefit provided by VAs. When consumers receive a tailored recommendation, they perceive that the information is accurate, which facilitates their purchase decision-making processes, consequently, increases their perceptions of the perceived value.

When forming value perceptions, consumers balance costs against benefits. Previous research into mobile transactions and online shopping has argued that cognitive effort is the main associated cost (Kleijnen et al. 2007). Cognitive effort has been defined as the total extent of the cognitive resources, such as perception, memory and judgement, needed to complete a task (De Barcelo Silva et al. 2020). Drawing on the information search literature, Lynch and Ariely (2000) found that cognitive effort represents an information search cost. Similarly, in the smart technology context, cognitive effort has been found to be a barrier in the way of VAs' adoption (De Barcelo Silva et al. 2020). Finally, based on recent works examining VAs (Cowan et al. 2017), we have included intrusiveness as a major cost for consumers, due to their "*always-on,*" listening feature. Technology intrusiveness has been defined as the extent to which a technology has the potential to monitor and surveille users by accessing their personal data (Lau et al. 2019). Several studies have shown that intrusiveness can cause reactance and avoidance (e.g. Baek and Morimoto 2012; Li et al. 2002), resulting in negative evaluations and the evocation of negative behavioural intentions towards the source triggering the reactance. Additionally, previous research has found that VAs that pose overly personal queries (i.e. that draw on private information), evoke in the user feelings of intrusiveness, which causes discomfort (Lau et al. 2019). In technology research, when a technology is perceived as intrusive, this can lead to a decrease in its perceived value (Benlian et al. 2020).

2.3 Social presence

Social presence has been described as "*the degree to which another individual stands out in an engagement*" (Short et al. 1976, p. 65). Chattaraman et al. (2019), in a study into robotics, found that the levels of social presence evoked by technologies/devices in service encounters are increasing. Social presence has been described as the extent to which computerised devices give people the impression they are in the company of another social entity (Van Doorn et al. 2017). Social presence-equipped devices may supplement or replace human service personnel, particularly when dealing with standard service requests. For instance, users can socially connect with their VAs to receive product information, rather than visit a store to get the same data. Social response theory (Reeves and Nass 1996) holds that individuals respond to media similarly to how they respond to other humans. The media accomplish this response through the use of social rules and two-way interactions. The language-based dialogues that take place between AI devices and their users possess a key human-like quality that evokes a sense of social presence in the consumer's consciousness, which influences him/her to interact with these artificial agents as (s)he would with humans (Chattaraman et al. 2019). Humans, due to technological advances that have taken place in recent years, are growing increasingly accustomed to participating in quasi-social relationships with AI 'beings' (Van Doorn et al. 2017).

Prior research (e.g. Forgas-Coll et al. 2022; Rosenthal-von der Pütten et al. 2016) demonstrated that the spoken language that AI devices use creates a strong sense of social presence. In addition, social response theory discusses the concept of reciprocity in the context of interactions between people and machines. Consumers "*take turns*" when they speak with VAs, that is, after speaking, they pause for the VA's response and then provide extended responses themselves (Cerekovic et al. 2017). In addition, when a consumer becomes accustomed to talking with a VA, (s) he begins to develop a rapport with the technology, just as (s)he would with other people (Cerekovic et al. 2017).

Moving beyond text-based customer interactions, the voice feature of VAs is a step closer to human-based service interactions, which significantly lowers the barriers for consumers to seek, and receive, at times they consider convenient, product recommendations. Voice-enabled technologies effectively promote social connecxions (Rosenthal-von der Pütten et al. 2016). In essence, voice-enabled interactions level the playing field between technology-based service providers and human service providers as social agents, as both are able to evoke social presence. In the same way that consumers connect with human service professionals, they can develop a social rapport with their VAs; this can allow the VAs to emit enhanced social cues consequently and the consumers can increase their engagement with the devices.

2.4 Engagement

The engagement concept has received extensive research attention in the last decade, with previous studies conceptualising the factor from two main perspectives. First, it has been analysed from a psychological perspective, as having cognitive and emotional aspects (Cheung et al. 2015). Psychological engagement has three elements: vigour, absorption and dedication: (i) vigour refers to the energy and psychological resilience of the consumer; (ii) absorption relates to the degree of attention the consumer pays and (iii) dedication refers to the extent of the feelings of significance, incentive and encouragement the consumer feels towards an entity (Cheung et al. 2015). Psychological engagement is important; psychologically engaged customers are more attached emotionally and cognitively, which, in the commercial context, converts them into very loyal customers to products/firms (So et al. 2014). On the other hand, customer engagement has been approached strictly from a behavioural viewpoint. Van Doorn et al. (2010) defined behavioural engagement as the proactive efforts that customers make on behalf of firms/brands, which affect the firms/brands in ways beyond the purchase itself.

Although in previous research the psychological perspective has been more widely endorsed, in the present study the behavioural approach is followed, for two reasons. First, the psychological conceptualisation commonly used in the literature does not focus on the main component of engagement, that is, behaviour (Van Doorn 2010), and it is degree of behavioural engagement that differentiates between highly engaged and not, or less, engaged consumers (Van Doorn et al. 2010). Second, the dimensions used to measure consumer engagement in psychology-based studies vary greatly. For example, So et al. (2014) employed a consumer engagement scale that included enthusiasm, attention, absorption, interaction and identification, whilst Hollebeek et al. (2014) used cognitive processing, affection and activation. This lack of consensus complicates the measurement and conceptualisation of consumer engagement.

Behavioural engagement has been conceptualised as the state where the consumer shows his/her preferences for a company/brand by posting positive messages about, and recommending, it to other consumers (Van Doorn et al. 2010). Moreover, it has been shown that behaviourally engaged consumers are more likely to adopt eWOM behaviours. For instance, Hollebeek et al. (2014) showed that engaged consumers are more likely to share their experiences, provide feedback and recommend products to other potential consumers. In summary, intention to recommend has been found to be a key dimension of behavioural engagement (Van Doorn et al. 2010), and previous research has tended to include it when operationalising behavioural engagement (e.g. Flavián et al. 2020).

The endorsement literature also relates behavioural engagement to consumers' intentions to follow recommendations and spread eWOM. For instance, a recent study showed that when consumers became engaged with a celebrity-endorsed e-cigarette advertised on Instagram, they became more likely to use the product (Phua et al. 2018). Similarly, Whang and Im (2021) recently showed that humans respond positively to VAs' recommendations. Furthermore, recent research has suggested that, compared to humans, AI agents, such as VAs, may not be perceived as having selfish intentions when making recommendations (Garvey et al. 2022). This perception may further develop trust between the AI and the consumer, which may encourage him/her to engage with the technology/device by accepting its recommendations (Lin et al. 2021). Overall, these trust-enhancing factors improve relationships, which is integral to the development of engagement, and the formation of intent to follow VAs' recommendations.

In addition, continuance intention to use has been identified as a form of consumer behavioural engagement. When consumers feel strong engagement with an object, they feel a strong willingness to maintain a relationship with it and, consequently, they invest time using, and continuously interacting with, the object. Prior research (e.g. Liébana-Cabanillas et al. 2018) analysed behavioural engagement types in the context of the use of mobile apps and found that intention to continue using the apps was the main engagement behaviour. In the context of MOOCs, it has been shown that when students become highly engaged with the online learning platform, they keep using it (Sun et al. 2020). In summary, in the VA context, consumers may become engaged with the technology with three behavioural intentions: to recommend VAs; to follow VAs' recommendations and to continue using VAs.

3 Hypotheses development

3.1 The influence of social presence on perceived benefits and costs

Social presence makes consumers feel that they are in the company of another social entity (Chattaraman et al. 2019). Research into interpersonal communications suggests that connectedness with others is grounded on the effortless communication that results from using convenient natural common language, nonverbal cues and interactivity speed (Cabibihan et al. 2014). In addition, cognitive neuroscience-based studies have found that face-to-face communication increases the individual's ability to process information effortlessly (Heninger et al. 2006). Arguably, when individuals are able to communicate easily with another entity, they consider this as convenient. Other technology-based research has suggested that users associate reduced effort in their interactions with technologies with increased convenience (Berry et al. 2002). Therefore, adapted to our framework, when individuals using a VA perceive that a recommendation is coming from a social entity and not from a machine, it is proposed that the recommendation will be easier to process, resulting in a convenient interaction.

The social presence associated with service robots evokes, in users, conspecific perceptions (Van Dorn et al. 2017). More particularly, social presence leads their users to perceive technological service agents as helpful, skilful and efficacious social entities. Similarly, social presence leads consumers to perceive robots as entities with human abilities, intentions and beliefs (Van Doorn et al. 2017). Thus, the robot begins to shift away from scenarios in which its user perceives it to be a machine and, instead, begins to perceive it as a real person "*that can create social and emotional connections with their human partners*'' (Cabibihan et al. 2014, p. 311); thus, the user develops a feeling of compatibility. Advice communication theory (MacGeorge et al. 2016) holds that people tend to seek advice from humans rather than from machines. More particularly, in face-to-face communication, individuals are more likely to seek advice from people who are similar to them (i.e. who have lived in similar circumstances). Accordingly, social presence may motivate individuals to feel compatible with VAs and receive recommendations in the much the same way as they would from real people (Chattaraman et al. 2019).

Humans are socially oriented beings, so when a technology/device evokes in them a perception of social presence, they apply social rules to the interaction, for example, by being polite and pausing for responses, just as they would in interpersonal interactions (Moon 2000). More specifically, it has been argued that VAs trigger feelings of social presence (Chattaraman et al. 2019), thus, when receiving recommendations from a VA, consumers tend to apply the same social rules they would apply when receiving recommendations from a real person. In-person communication is synchronous and subject to turn-taking rules. Each individual takes his/her turn to speak, and then lets the other speak in turn, which leads the interlocutors to fully engage in the interaction, and each perceives the points being made are being targeted at him/her. In addition, interpersonal communication is often one to one, and not one to many, with messages being directed at a specific individual. In this case, the communication might be perceived as personalised. Social presence, in this instance, might lead consumers to perceive the VA as a real person, giving personalised recommendations.

Based on these points, the following hypotheses about the effect of social presence on the perceived benefits of VAs are proposed:

H1 The social presence of a voice assistant has a positive effect on its perceived convenience.

H2 The social presence of a voice assistant has a positive effect on its perceived compatibility.

H3 The social presence of a voice assistant has a positive effect on its perceived personalisation.

Wang et al. (2007) argued that social presence is made up of intimacy and immediacy. Intimacy refers to the feeling of being in a close personal association and of belonging. Adapted to the technology context, the connecxion and the sense of belonging developed through intimacy leads consumers to perceive technologies as human beings (Van Dorn et al. 2017). Interpersonal communication theory-based (Jehn and Shah 1997) studies have shown that individuals use less cognitive effort in human–human interactions than in human–machine interactions because they perceive that their human counterparts think and interact as they do, which makes them feel more comfortable and promotes fluid communications.

Second, immediacy reflects the psychological distance between a communicator and the recipient of the communication (Wang et al. 2007). In the technology context, immediacy relates to how readily technologies can exchange information with their users. Immediacy leads to high interactivity, which can increase the effectiveness of communication (e.g. accuracy and quick responses) and, consequently, reduces the cognitive effort needed to understand communications. Furthermore, in communication-education research, Christophel (1990) reported that instructors with higher immediacy were viewed as more positive and effective, which decreased the mental effort students needed to assimilate course materials.

Previous studies have provided evidence that the feelings of social presence triggered by computers makes individuals perceive the devices are "*socially present*," which results in them applying social norms in their interactions, and establishing familiar and personal connections, with the devices (Verhagen et al. 2014). The feeling of familiarity and personal connexion created through social presence may lead consumers to perceive their VAs as friends rather than as perpetrators (Qiu and Benbasat 2009), which increases their likeability and trustworthiness (Benlian et al. 2020), which can override feelings of intrusiveness. Moreover, Kim and McGill (2011) argued that, as people feel more powerful when interacting with social entities than with machines (because social entities are subject to social processes), when dealing with VAs (and in this context, they perceive VAs to be social entities) they feel they have more control, which reduces their behavioural uncertainty and intrusiveness concerns vis-à-vis the machines.

Applying this logic to the context of VAs, we argue that the social presence of VAs attenuates their intrusive effects.

Based on these points, we propose the following hypotheses regarding the effect of social presence of VAs on their perceived costs:

H4 The social presence of a voice assistant has a negative effect on the perceived cognitive effort needed to use it.

H5 The social presence of a voice assistant has a negative effect on its perceived intrusiveness.

3.2 The influence of perceived benefits and costs on perceived value

Research into innovative technologies has identified convenience as a benefit and, thus, a decisive reason for adopting a given service (Ukpabi and Karjaluoto 2017). Scholars have argued that convenience is at the forefront of consumers' evaluations of services and of their behaviours (Berry et al. 2002). People derive value from convenient and efficient service delivery. For example, the perceived value of mobile services is primarily driven by their degree of effectiveness and efficiency in achieving goals/tasks (Kleijnen et al. 2007). In the voice-based technology context, it has been argued that VAs provide customers with great value because of their convenience and speed; thus, they are regarded as a very innovative and valuable technology (Klaus and Zaichkowsky 2020). Ukpabi and Karjaluoto (2017) argued that consumers feel it is often easier and more convenient to use voice input than to type, one reason being that voice input is considered to require less effort. In particular, when a VA hears the keyword, it absorbs the user's voice, interprets his/her language and processes a response, all in real time, without any additional effort on the part of the user (Grover et al. 2020). In addition, VAs give recommendations based on the consumer's historical preferences and habits, to which it has access through its algorithm-based functionality. Thus, the consumer has access to quick, effortlessly obtained information, which may increase his/her perceptions of the value (s) he derives from the system (Ukpabi and Karjaluoto 2017).

The VA's voice function allows consumers to conduct conversations that are similar to those they conduct in face-to-face interactions. With their voice characteristic and AI features, VAs can mimic humanistic natural language, address the consumer's requests and offer suggestions for products or services. In this case, VAs act like human recommendation agents in a real shop/store (McLean et al. 2021); consequently, people perceive that a kind of similarity exists between the agents, the VAs and shop assistants. In addition, due to the personalised services that VAs offer (e.g. tailored recommendations, customised products), consumers may feel they possess human intellectual ability and intelligence. Data from 2017 found that 41% of people who owned VAs said they felt comfortable communicating with the devices and that they experienced a feeling of compatibility between themselves and the technology (Park et al. 2018). This perceived compatibility may increase consumers' perceptions of the value of VAs.

One of the most important personalised services in new media communications is product recommendations (Rhee and Choi 2020). The fundamental idea behind personalisation is that each consumer should be treated as a unique entity and, thus, recommendations should be designed to fit his/her preferences (Komiak and Benbasat 2006). Messages that match the consumer's preferences have been argued to be perceived as stronger and more useful than standardised, non-matched messages (Ho and Bodoff 2014). By addressing consumers at the individual, rather than at the "*mass*", level, personalisation builds deeper one-to-one company-consumer relationships, which enhances their perceptions of service quality and value (e.g. Hagel and Rayport 1996). Moreover, personalisation increases consumers' well-being, improves their decision-making and helps them perform tasks more quickly (Komiak and Benbasat 2006). Similarly, in the VA context, personalisation boosts cross-selling, which decreases consumers' search efforts, which may lead them to regard VAs as valuable (Hernandez-Ortega and Ferreira 2021).

Based on the above points, we propose the following hypotheses about the effects of the perceived benefits of VAs on the perceived value of their recommendations:

H6 The perceived convenience of a voice assistant has a positive effect on the perceived value of its recommendations.

H7 The perceived compatibility of a voice assistant has a positive effect on the perceived value of its recommendations.

H8 The perceived personalisation of a voice assistant has a positive effect on the perceived value of its recommendations.

Complex technologies require high cognitive effort to operate (Cowan et al. 2017). VAs often make functional errors by failing to understand consumers' commands when they feature disfluent speech, such as stuttering, false syntactic structures and erroneous articulation (Kim and Choudhury 2021). For example, Cowan et al. (2017) suggested that Siri users perceive they expend a high cognitive effort when Siri does not fully understand what they say. Furthermore, Kim and Choudhury (2021) found that VAs struggled to understand indexical terms such as "*here*" and "*it,*" which caused their users to expend more cognitive effort. In the same vein, Lee et al. (2019) argued that VAs receive more than just simple queries from consumers, they also receive emotional inputs (e.g. aggressive tones). VAs' inability to understand context and consumers' emotional states may increase the cognitive effort their users expend in their interactions; consumers perceive this expenditure as one of the biggest cognitive costs of these systems and this diminishes the perceived value of their services.

Technology intrusiveness relates to the degree to which a technology enables individuals to be reachable (Benlian et al. 2020). In the technology context, it has been found that when a technology is perceived as intrusive, the perceived value of the technology decreases (Lau et al. 2019). VAs can be considered as potentially highly intrusive, as they have to constantly listen out for the users' wake-up keyword in order to be activated and can, erroneously, unintentionally, activate their microphones (Lau et al. 2019). Unintentional voice activations have been found to increase consumers' feelings of invasion and intrusiveness, because they suspect that VA operators might be inconspicuously collecting information about them and their behaviours to create detailed consumer profiles that they might share with third-party service providers (Jeon et al. 2020).

Based on the above points, we propose the following hypotheses about the effects of the perceived costs of VAs on the perceived value of their recommendations:

H9 The perceived cognitive effort associated with a voice assistant has a negative effect on the perceived value of its recommendations.

H10 The perceived intrusiveness associated with a voice assistant has a negative effect on the perceived value of its recommendations.

3.3 The influence of perceived value on engagement

Hollebeek et al. (2014) claimed that consumer engagement behaviours are consequences of perceived value. For example, when users perceive they have received a high degree of value from a consumption experience, they are more prone to engage in behaviours related to the experience, such as providing reviews, recommendations and referrals. In mobile services' research, it has been found that the more that consumers valued using the mobile service, the more likely they were to spread positive eWOM (Cheshin et al. 2018). Therefore, when consumers perceive they are receiving great value from their VAs, they are more likely recommend them. Similarly, prior studies have found that consumers' adoption of eWOM behaviours is an outcome of the value they perceive they derive from online platforms (Chen et al. 2017). When users perceive that a social media platform is valuable, they are more likely to adopt the recommendations made on the platform. In addition, it has been found that the perceived value of mobile apps exerts a direct and positive impact on consumers' intentions to use the information they provide (Cheshin et al. 2018). Thus, as perceived value increases, we expect that the consumer's intention to adopt VAs' recommendations will increase. In the same vein, previous research has identified that a positive relationship exists between perceived value and continuance use intention in different contexts, such as digital music and blogs (Pal et al. 2021) and smart healthcare devices (Lee and Lee 2020). When the consumer positively perceives the value (s)he has obtained from a product, (s)he believes that its benefits outweigh its costs, such that it makes sense to continue using the product. In the VA context, when consumers perceive they derive value from using the device, they form a positive perception towards it which leads them to continue to use it. Based on the above points, we expect that, when consumers perceive they have received value from the recommendations made by their VAs', all three components of consumer engagement, that is, intentions to follow the VAs' recommendations, to recommend the VA and to continue using the VA, will be enhanced, and propose the following hypothesis:

H11 The perceived value of voice assistants' recommendations has a positive effect on consumer engagement with these voice assistants.

4 Research methodology

4.1 Data collection

To test the hypotheses a quantitative study was undertaken with VA users. The participants were US residents recruited through an online panel, a market research company assisted in the process. The survey took between 10 and 12 min for the participants to complete. The data were collected in November 2021 involving 423 panel members participating voluntarily. To take part, the participants had to have used a VA to access product/service recommendations at least once. To ensure this was the case, a qualifier sentence was included in the survey to guarantee that the participants were VA users and, in addition, they were posed a question to ensure they belonged to the segment under study ("*How often do you use VAs to get recommendations*?"). Only respondents who had, at least once, used VAs to obtain recommendations, could continue with the questionnaire, thus ensuring the reliability of the responses. Moreover, we controlled for the average response times it took for the participants to complete the questionnaire. Respondents who answered the check questions too quickly were eliminated (Barge and Gehlbach 2012).

A total of 316 valid responses were obtained; therefore, in the sample of VA users, 74.7% confirmed they used VAs to obtain recommendations. Of the respondents, 48.73% were men, 51.59% were aged between 18 and 30, and 50% had an undergraduate degree (Table 1 includes more detailed socio-demographic information about the participants). Some 42.42% of the participants used the Alexa (Amazon) VA and 28.62 used Siri (Apple). Regarding the participants' VA experience, 55.22% had been users for more than 3 years. In addition, it should be highlighted that 56.5% of participants said they frequently used VAs to obtain product and service recommendations.

The information was obtained through a questionnaire using closed questions. The research constructs were operationalised using items adapted from previous research (see Table 3). The variables were measured using 7-point Likert scales, where 1 indicated "*strongly disagree*" and 7 "*strongly agree.*" All constructs were considered as first-order and reflective, except for engagement, which was considered as a second-order formative construct. A pre-test of the questionnaire was carried out to address any possible defects and to identify problems that might arise during the information-gathering process. The surveys were administered on 20 regular VA users. These respondents had similar characteristics to the target sample. In the pre-test the respondents were asked to complete the questionnaire. As a result of the pre-test, some of the scales were adapted to increase their understanding and to

Table 1 Sample description

	Frequency	%
Gender		
Male	154	48.73
Female	159	50.32
Prefer not to say	3	0.95
Age		
18–25	111	35.13
26–30	52	16.46
31–35	51	16.14
36–40	37	11.71
41–45	24	7.59
46–50	13	4.11
51–55	12	3.80
56–60	6	1.90
61–65	4	1.27
66 and over	6	1.90
Education level		
Primary school	2	0.63
High/secondary school diploma	92	29.11
Undergraduate degree	158	50.00
Graduate degree	64	20.25
Citizenship		
USA	300	94.94
Other	16	5.06

avoid erroneous interpretations. In addition, we applied procedural remedies to minimise the risk of common method variance, randomly counterbalancing the stimuli order, interspersing irrelevant, trivial questions with the relevant questions used to measure the survey items, promising complete anonymity and by positioning the demographic questions at the end of the questionnaire (Podsakoff 2003).

4.2 Estimation procedure: two-step approach, PLS-SEM

The data was analysed using partial least squares (PLS) structural equation modelling (SEM), with SmartPLS 3.0 software (Ringle et al. 2015). The PLS-SEM approach was selected for the following reasons. First, the approach has been widely followed in recent research (e.g. Mishra et al. 2022) and is found on component-based structural equation modelling (Hair et al. 2011). Second, PLS-SEM is able simultaneously to deal with higher-order constructs and mediation in a single model (Sarstedt et al. 2019). In this study, we have proposed engagement as a second-order formative construct. Moreover, PLS is recommended for prediction-based models designed to identify key predictor or driver constructs (Hair et al. 2011), which aligns with the research objectives of this study.

As aforementioned, engagement is proposed in this study as a second-order formative construct, which is measured by three first-order reflective constructs (i.e. the dimensions of engagement, intention to recommend the VA, intention to follow the recommendation of the VA and intention to continue using the VA). Second-order constructs were proposed from a methodological standpoint because they reduce the number of hypothesised relationships in a model, making it more parsimonious (Thien 2020). This also serves to reduce collinearity issues (Sarstedt et al. 2019), makes results easier to interpret and helps generate reliable and valid empirical results (Thien 2020). In summary, the first-order constructs were measured reflectively, by their own measurement items, whereas the second-order construct was measured formatively, by its first-order reflective constructs, using a two-stage approach (Sarstedt et al. 2019).

Specifically, a two-step approach was followed, as suggested by Becker et al. (2012) to test the higher-order reflective-formative construct. In the first step, we took a repeated indicator approach to obtain the latent variable scores of the first-order constructs used to measure engagement. In the second step, the latent variable scores obtained previously were included as the measures of engagement, and we calculated their weights and significance. The collinearity of the indicators [based on their variance inflation factors (VIFs)] and the significance of the indicator weights were used to determine the formative measure. The results of this process are shown in Table 2. The VIF values were below the 3.3 threshold (Hair et al. 2011), thus collinearity is not a serious concern in this study. We used a 5000 resample bootstrapping technique to assess the significance of the weights, and the results showed that they were significant at the $p<0.001$ level. This demonstrates that the three components (the behavioural intentions) are correlated with the main engagement construct.

4.3 Measurement validation

Once the latent variable scores had been obtained (to measure engagement), a confirmatory factor analysis was carried out to confirm the dimensional structure of

Table 2 Assessment of the higher-order construct

Higher-order construct	Formative indicators	Outer weights	VIF	*t* value
Engagement	Intention to continue using the VA	0.363	3.069	50.597***
	Intention to recommend the VA	0.363	3.143	49.525***
	Intention to follow the recommendations of the VA	0.353	2.903	57.093***

As previously explained, the latent variable scores of the first-order constructs (calculated in a prior step) were used to measure engagement. Behavioural intentions were measured using three items: continuance intention to use (adapted from Bhattacherjee 2001), intention to recommend (adapted from Casaló et al. 2017) and intention to follow the recommendation (adapted from Cheung et al. 2009). All these measures comply with the validity requirements of the previous step

VIF Variance Inflation Factor

***$p<0.001$

Table 3 Reflective measurement scales

Items	Factor loadings
Social Presence (Chattaram et al. 2019) α = 0.953; CR = 0.963; and AVE = 0.811	
When receiving recommendations from the VA, I feel like they are face-to-face recommendations	0.843
When receiving recommendations from the VA, I feel a sense of human contact	0.928
When receiving recommendations from the VA, I feel a sense of sociability	0.908
When receiving recommendations from the VA, I feel a sense of human warmth	0.913
When receiving recommendations from the VA, I feel a sense of human sensitivity	0.921
When receiving recommendations from the VA, I feel a sense of realism and belonging	0.889
Convenience (Tan and Liao 2021) α = 0.700; CR = 0.868; and AVE = 0.767	
It is convenient to me to get recommendations from the VA	0.904
I do not take much time to understand recommendations given by the VA	0.847
Compatibility (Goodhue and Thompson 1995) α = 0.939; CR = 0.961; and AVE = 0.892	
Using VAs to obtain recommendations fits my needs	0.925
Using VAs is compatible with the way I normally obtain recommendations	0.948
Using VAs to obtain recommendations is in line with my preferences	0.959
Personalisation (Komiak and Benbasat 2006) α = 0.935; CR = 0.954; and AVE = 0.838	
I feel the VA understands my needs when making recommendations	0.907
I feel the VA knows what I want when making recommendations	0.936
I feel the VA takes my needs as its own preferences when making recommendations	0.894
I feel the VA matches with my interests when making recommendations	0.923
Cognitive effort (Dabholkar and Bagozzi 2002) α = 0.935; CR = 0.958; and AVE = 0.884	
Receiving recommendations from the VA is complicated	0.937
Receiving recommendations from the VA is difficult	0.954
Receiving recommendations from the VA involves a lot of effort on my part to understand them	0.931
Intrusiveness (Lau et al. 2019) α = 0.919; CR = 0.949; and AVE = 0.861	
Whilst receiving recommendations from the VA, I feel I am under surveillance	0.936
Whilst receiving recommendations from the VA, I feel I am being monitored	0.959
Whilst receiving recommendations from the VA, I feel it is listening to everything around me	0.887
Perceived value (Liu et al. 2015) α = 0.955; CR = 0.967; and AVE = 0.881	
I believe that using the VA to obtain recommendations is valuable	0.929
I believe that using the VA to obtain recommendations is worthwhile	0.946
I believe that using the VA to obtain recommendations is beneficial	0.940
Overall, using the VA to obtain recommendations delivers high value	0.940

the scales. Specifically, for reflective constructs, we examined the factor loadings to make an initial assessment of the internal consistency of the constructs. All factor loadings exceeded the 0.7 threshold (Henseler et al. 2009) as regards their respective

Table 4 Discriminant validity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Social Presence (1)	**0.901**							
Convenience (2)	0.327	**0.876**						
Compatibility (3)	0.473	0.708	**0.944**					
Personalisation (4)	0.548	0.616	0.679	**0.915**				
Cog. Effort (5)	−0.010	−0.373	−0.199	−0.275	**0.940**			
Intrusiveness (6)	−0.152	−0.292	−0.272	−0.303	0.170	**0.928**		
Value (7)	0.541	0.647	0.686	0.705	−0.252	−0.376	**0.939**	
Engagement (8)	0.546	0.643	0.734	0.702	−0.267	−0.389	0.871	–

Diagonal elements (in bold) are the squared roots of the AVEs. Correlations are the off-diagonal elements

constructs (see Table 3). The reliability of the measures was then analysed using composite reliability (CR). The CR values are shown in Table 3; they exceed the recommended value of 0.7 (Hair et al. 2011). Similarly, the Cronbach's α values exceeded the recommended 0.7 threshold for all reflective constructs, as can also be seen in Table 4. Convergent validity was assessed using average variance extracted (AVE), which should be greater than 0.5 (Fornell and Larcker 1981). The results shown in Table 3 show that this criterion was met. Finally, the results shown in Table 4 confirm the discriminant validity of the measures, as the square roots of the AVEs of the constructs are greater than their corresponding inter-construct correlations (Fornell and Larcker 1981).

5 Results

5.1 Structural model: direct effects

Having confirmed the reliability and validity of the measurement scales and the dimensionality of the constructs, we next evaluated the direct effects proposed in the research model using PLS, again with SmartPLS software version 3.0. The path relationships and the R^2 values of the endogenous latent variables were initially assessed and a bootstrapping procedure with 10,000 subsamples was conducted to calculate the statistical significance of the path relationships.

We found support for nine of the eleven hypotheses (H4 and H9 rejected) (see Fig. 2). It was found that social presence is a strong predictor of the benefits of VAs', including convenience ($\beta = 0.327$, $p < 0.001$), compatibility ($\beta = 0.473$, $p < 0.001$) and personalisation ($\beta = 0.548$, $p < 0.001$); hence, H1, H2 and H3 are supported. On the other hand, it was found that social presence was negatively related to (the cost of) intrusiveness ($\beta = -0.152$, $p < 0.001$) and did not affect cognitive effort expended ($\beta = -0.010$, $p > 0.05$); hence, H5 is supported and H4 is rejected.

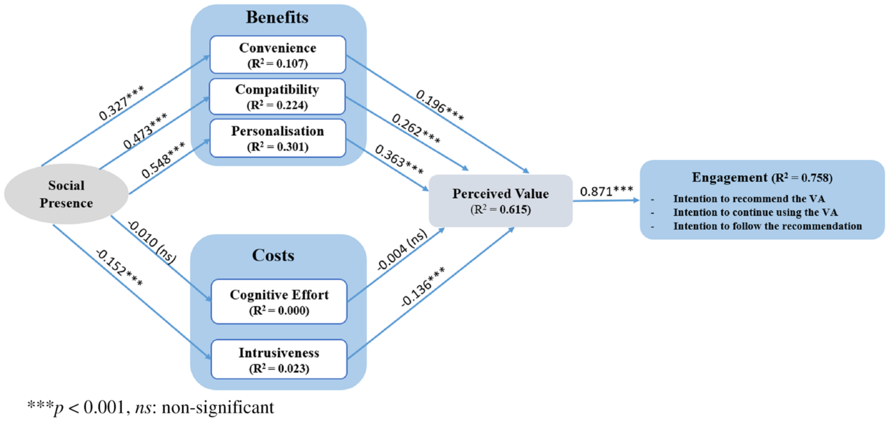

Fig. 2 Structural analysis of the research model

It was found that personalisation is the strongest determinant of the perceived value of VAs' recommendations (β = 0.363, $p < 0.001$). Convenience (β = 0.196, $p < 0.001$), and compatibility (β = 0.262, $p < 0.001$) also positively influenced perceived value. In contrast, intrusiveness (β = − 0.136, $p < 0.001$) was seen to have a negative effect on perceived value. Cognitive effort was observed to have a non-significant effect (β = − 0.004, $p > 0.05$) on perceived value. Therefore, H6, H7, H8 and H10 are supported and H9 is rejected. Last, the perceived value of VAs' recommendations had a great impact on engagement (β = 0.871, $p < 0.001$), supporting H11.

As to the explanatory power of the research model, it partially explains the study's main endogenous variables, perceived value ($R^2 = 0.615$) and engagement ($R^2 = 0.758$). According to Chin (1998), these findings suggest that the R^2 values are moderate to substantial.

5.2 Indirect effects

The results suggested that social presence and benefits (convenience, compatibility, personalisation) and costs (cognitive effort, intrusiveness) may have indirect effects on perceived value and engagement. Therefore, these potentially mediated relationships were analysed following Chin (1998) and Zhao et al. (2010), that is, by calculating the bias-corrected and accelerated confidence intervals of the effects. To do so, we used 10,000 subsamples, with no sign change. Table 5 shows the results of these analyses. The results show that, as to the benefits of VAs, convenience, compatibility and personalisation had significant positive indirect effects on engagement through perceived value. Turning to the costs, whilst intrusiveness significantly negatively influenced engagement via perceived value, perceived value did not mediate the effect of cognitive effort on engagement. In addition, social presence exerted a positive indirect effect on perceived value via perceived benefits (convenience, compatibility, personalisation) and intrusiveness. However, cognitive effort did not

Table 5 Indirect effects

Indirect paths							Path coeff	Sig
Social Presence	→	Convenience	→	Value			0.064*	0.014
Social Presence	→	Compatibility	→	Value			0.124***	0.000
Social Presence	→	Personalisation	→	Value			0.199***	0.000
Social Presence	→	Convenience	→	Value	→	Engagement	0.056*	0.014
Social Presence	→	Compatibility	→	Value	→	Engagement	0.108***	0.000
Social Presence	→	Personalisation	→	Value	→	Engagement	0.173***	0.000
Social Presence	→	Intrusiveness	→	Value			0.021*	0.049
Social Presence	→	Cog. Effort	→	Value			0.000n.s	0.986
Social Presence	→	Intrusiveness	→	Value	→	Engagement	0.018*	0.050
Social Presence	→	Cog. Effort	→	Value	→	Engagement	0.000n.s	0.987
Convenience	→	Value	→	Engagement			0.171**	0.002
Compatibility	→	Value	→	Engagement			0.229***	0.000
Personalisation	→	Value	→	Engagement			0.316***	0.000
Cog. Effort	→	Value	→	Engagement			−0.003n.s	0.918
Intrusiveness	→	Value	→	Engagement			−0.119***	0.000

n.s. Non-significant effect

***$p < 0.001$; ***$p < 0.01$*; *$p < 0.05$;

mediate this relationship. Finally, social presence was seen to exert a positive indirect effect on engagement. In this case, the three benefits and intrusiveness, first, and perceived value, second, sequentially mediated this indirect effect. Again, the indirect effect of social presence on engagement via cognitive effort was not seen to be significant.

6 Discussion and implications

6.1 General discussion

Consumers are increasingly using AI-based devices, such as VAs, to obtain product and service recommendations. Focusing on VAs, this study explains how the perceived value derived from these recommendations is formed, the main consequences of this value and provides a guide for practitioners by highlighting the important features that must be taken into account in VA design. To do so, we combined social presence (e.g. Van Doorn et al. 2017), the cost–benefit paradigm (Kleijnen et al. 2007), perceived value (Zeithaml et al. 2020) and consumer engagement (Hollebeek 2011; Hollebeek et al. 2014). Specifically, the study's results revealed, first, the benefits and costs that determine the perceived value of VAs' recommendations. In this respect, positive relationships between convenience, compatibility, personalisation and the perceived value of VAs' recommendations were found. In particular, perceived value was found to be strongly influenced by personalisation, a result in line with Hagel and Rayport (1996) and Hernandez-Ortega and Ferreira (2021), who suggested that personalisation enhances the value of consumers' experiences. In the same vein, Ho and Bodoff (2014) highlighted that personalised IT services offer the right content, in the right form, to the right user, at the right time and location. Conversely, intrusiveness negatively influences the perceived value of VAs' recommendations. Interestingly, although prior research has often identified cognitive effort as the strongest impediment in human–robot interactions (Cowan et al. 2017), the present study found that cognitive effort was an insignificant cost in the context of VAs. This may be because the study participants were heavy users of VAs; however, cognitive effort may be more important in the initial usage stage, when individuals are more likely to perceive technology as complicated to use and requiring mental effort (Davis 1989).

Second, social presence was found to be an important predictor of the aforementioned benefits (i.e. convenience, compatibility, personalisation) and negatively related to the cost of intrusiveness. Furthermore, the study showed that social presence influences indirectly, via costs and benefits, the perceived value of VAs' recommendations. Cabibihan et al. (2014) argued that consumers can be easily persuaded by people with whom they have close relationships and with whom they feel connected. As consumers gain a sense they are in a social relationship—through social presence—with their VAs, the devices perform the role of a peer consumer by providing recommendations and product information.

Finally, it was found that that the perceived value of VAs' recommendations may, in general, increase consumer engagement with the devices. In addition, as the approach taken to measure consumer engagement in this work is based on brand engagement in the social media context (Hollebeek 2011; Hollebeek et al. 2014), we also validated a consumer engagement scale in the context of VAs, which consists of three behavioural intentions: (1) to recommend the VA; (2) to continue using the VA and (3) to follow the recommendations of the VA.

6.2 Theoretical implications

To better understand the background of the perceived value of, and consumers' engagement with, VAs' recommendations, the present study followed the cost–benefit paradigm (Kleijnen et al. 2007), integrating the social presence concept (Van Doorn et al. 2017), to develop a conceptual model, the results of which contribute to contemporary research into VAs and shed light on this emerging topic in three ways.

First, we included social presence in the conceptual model as it has been shown to be one of the main determinants of consumers' perceptions of the benefits and costs of the perceived value of VAs. The results suggested that social presence is an important predictor of benefits, including convenience, compatibility and personalisation, which is consistent with the findings of previous studies in the psychology and communication literature (MacGeorge et al. 2016). More specifically, the study found strong empirical evidence that social presence is an important driver of personalisation. This finding is supported by implicit personality theory (Verhagen et al. 2014), which proposes that agents that create a feeling of social presence and mutual connexion are likely to increase the feeling that the content they offer is appropriate. Regarding convenience, the results extend, in the context of VAs, the findings of previous cognitive neuroscience studies that suggested that social presence increases the individual's ability to effortlessly and easily process information (Heninger et al. 2006). As to compatibility, our findings support Van Doorn et al. (2017), who suggested that the more closely that social presence resembles a human, the more consumers may infer a device has human characteristics (e.g. warmth and competence), which may lead them to perceive VAs as social entities, similar to them. Whereas, social presence was found to be negatively related to intrusiveness, a cost. This suggests that when consumers perceive a device to have a high degree of social presence, they may worry less about its intrusiveness, because they may regard it as a trustworthy person, rather than as a machine. In turn, the study did not find any significant relation between social presence and cognitive effort. A possible explanation for this is that consumers may perceive that VAs trigger social presence, but that perception may be limited to their intrusiveness and privacy aspects and, thus, social presence may not mitigate functional aspects, such as cognitive effort.

Second, whilst VAs have been one of the most interesting research topics in the information systems (IS) field over the past decade, most prior research has examined their initial stages of adoption and usage (e.g. Park and Ohm 2014) and relatively little is known about consumers' perceptions of the value of VAs when they are used to obtain product/service recommendations. The present study, indeed, is the first to develop a model which explains the benefits and the costs involved in the value creation process when users obtain recommendations from VAs. The analyses provide strong support for the conceptual model. In particular, the results showed that personalisation is the strongest determinant of perceived value. This finding is in accordance with the view that personalisation is the overarching characteristic of VAs (e.g. Rhee and Choi 2020; Pal et al. 2021). This suggests that consumers perceive great value in their VAs when they receive personalised recommendations. This finding extends into the VA field the results of previous research in other contexts, such as websites (Ho and Bodoff 2014), mobile services (Wang et al. 2020), IS (Hagel and Rayport 1996) and augmented reality (Lau et al. 2019). In addition, it was shown that convenience positively influences perceived value. If consumers perceive that obtaining recommendations from VAs is effortless and quick, they perceive they are receiving greater value. This result is in line with previous research which suggested that convenience is a benefit that drives users to perceive value in innovative technologies (Ukpabi and Karjaluoto 2017). In addition, perceptions of higher compatibility create higher perceptions of the value of VAs. This relationship was confirmed previously by Kleijnen et al. (2007) in the context of mobile services and Rauschnabel et al. (2015) in the context of smart glasses. Value perceptions about new technologies have traditionally been linked to the compatibility of the systems. Indeed, our findings show that this relationship pertains also within the context of VA technologies.

Moreover, the study results emphasised the importance of intrusiveness as an inhibitor, which works against the maximisation of the perceived value of the recommendations made by VAs. The core rationale behind this relationship is that intrusive technological features lead consumers to fear that their private information might be stolen from the VA or that the companies that hold their data will use it for purposes other than that originally intended. This fear stops consumers using the technology. In the same vein, this result supports the results of previous smart technology-based research (Lau et al. 2019), which found that intrusiveness leads consumers to regard the technology as lacking value. In contrast, cognitive effort was not found to constitute a significant cost in terms of its influence on perceived value. This result is surprising, because previous research in the innovation theory domain has often argued that cognitive effort is the strongest impediment in human–robot interactions (Cowan et al. 2017). However, in the present study it is proposed that this surprising finding may have two explanations: First, the current generation of VAs may be technologically far superior and feature a variety of novel skills that improve their functions and technical aspects (e.g. neural text-to-speech technology [NTTS]), which may mitigate perceived cognitive effort and, second, AI digital assistants are no longer new technology-based products and users are accustomed to the devices. This is consistent with the TAM, that is, individuals perceive technologies to be complicated to use, and requires mental effort to operate, in the initial usage stage (Davis 1989).

Third, the present study examines how the perceived value of VAs' recommendations affects consumer engagement. The greater the value consumers perceive they derive from their VAs, the more likely they are to feel comfortable in using the devices, which can trigger engagement behaviours. This outcome is consistent with previous studies which confirmed that a positive association between perceived value and consumer engagement exists, for example, in virtual communities (Chen et al. 2017; Hsu and Lin 2016). Moreover, whilst previous studies have suggested that intention to spread eWOM and intention to continue to use are two of the indicators most commonly used to measure behavioural engagement with technologies (Pal et al. 2021; Moriuchi 2019), the present study adapts this academic understanding of consumer behavioural engagement to the specific context of VA recommendations by adding a third dimension, eWOM adoption, that is, the intention to follow the recommendations made by VAs.

6.3 Practical implications

The study's findings also have implications for practitioners and other stakeholders who wish to increase the value of VAs. In practice, the results can help service providers and VA developers understand how VAs should be designed to enhance their value and consumer-VA engagement. First, practitioners should focus on the key factor that drives the perceived value of VAs' recommendations, that is, social presence. VA designers should, for instance, integrate informal and natural speech into the devices using greetings, valedictions, even names, make them able to listen, express warmth, show concern for the consumer and understand the queries (s)he raises.

Second, this research examines the role of the main costs and benefits associated with VAs. Specifically, the findings suggested that personalisation is the most important benefit and intrusiveness is the most important cost. On the one hand, this suggests that service providers should strongly focus on the VA's personalisation feature by increasing their use of machine learning and AI technologies; this might allow them to more efficiently collect and analyse data about consumers' preferences, including product preferences. In addition, VA developers might introduce social analytic techniques, such as sentiment analysis and opinion mining, which could make the consumers co-creators of their own personalised recommendations. On other hand, VA developers can reduce intrusiveness, for instance, by allowing their users to mute the devices with voice commands. These commands could set a time duration (e.g. "*Hey Google, stop listening for the next hour*"), after which the device might announce that it is listening again. Similarly, service providers might more clearly explain to users that the VA's audio logs can be deleted from interaction history (as with web browsers). In addition, allowing consumers to manually activate "*incognito*" mode, either through a voice command or through the companion app (e.g. Amazon App for Alexa), may make them feel more comfortable making requests involving private information, because they know the request will not be saved as an audio log/command. Third, the study highlighted the important role of compatibility in generating perceived value. Thus, VA designers should make the devices more human like by developing their voice features and AI capabilities to help them understand and interpret consumers' instructions in a natural way. We expect, for instance, that improving the tonal quality of VAs' voices and supporting different languages, would make users feel a greater sense of compatibility between themselves and their VAs. These steps would, indubitably, increase their recommendations' perceived value.

Finally, practitioners should take into account the aforementioned actions to maximise the perceived value of the recommendations made by VAs, as this is crucial for increasing engagement. In the present study, perceived value predicted 75.8% of consumer engagement with VAs. If practitioners can increase the perceived value of VAs' recommendations, they may potentially better fulfil consumers' needs, who may, consequently, develop higher levels of engagement with the VAs in terms of increased intentions to recommend, continue using and to follow their recommendations. These practical implications, the study's theoretical implications and the main results of the research are summarised in Table 6.

6.4 Limitations and directions for future research

In spite of its interesting results, this study has limitations that offer opportunities for future research into AI-based technologies, in general, and VAs in particular. First, the research was conducted based on general recommendations made by VAs. The empirical model should also be tested on recommendations about specific products/services or on specific information searches. For example, the relative importance of the antecedents of perceived value, and its influence on consumer engagement, may depend on the type of product/service recommended (e.g. hedonic vs. utilitarian products/services). Second, whilst the study sheds light on the main benefits and costs associated with the perceived value of VAs, other key variables might be examined. For example, as an AI-based device, future research might explore the

Table 6 Summary of results and implications

Main results	Theoretical implications	Practical implications
-The convenience, compatibility and personalisation of VAs positively influence the perceived value of their recommendations (H6, H7 and H8 supported) -The cognitive effort cost of VAs does not influence the perceived value of their recommendations (H9 rejected) - The intrusiveness cost of VAs negatively influences the perceived value of their recommendations (H10 supported)	- Extends the cost–benefit paradigm, widely applied in other contexts [e.g. websites (Ho and Bodoff 2014), mobile services (Wang et al. 2020) and augmented reality (Lau et al. 2019)], to the context of VAs	- VA designers should maximise their convenience, compatibility and personalisation and minimise their intrusiveness. For example, by: * Collecting and analysing data about user preferences, including product preferences * Introducing sentiment analysis, visual analytics and opinion mining * Enhancing VAs' human-like features, for example, in their voice function and cognitive capabilities * Reducing the intrusiveness of the devices by clearly explaining to users that audio logs can be deleted from interaction history and by introducing an incognito mode
- The social presence of VAs positively affects their convenience, compatibility and personalisation (H1, H2 and H3 supported) - The social presence of VAs does not affect their perceived cognitive effort (H4 rejected) - The social presence of VAs negatively affects their intrusiveness (H5 supported)	- Based on cognitive neuroscience studies (Heninger et al. 2006), we found that social presence increases convenience - Based on implicit personality theory (Verhagen et al. 2014), we found that social presence increases feelings of personalisation - Based on the literature on the perceived risks and privacy of technologies (Lau et al. 2018; Manikonda et al. 2018), we found that the social presence of VAs mitigates their perceived intrusiveness - The role of the social presence of automated technologies in generating value for technologies is confirmed, in line with previous theoretical proposals (e.g. Van Doorn et al. 2017)	- VA designers should focus on: * Enhancing natural and intuitive conversations and establishing a bond with consumers * Including informal and natural speech, for example, using greetings, valedictions, or even names * Developing devices which can listen, express warmth, show concern for the consumer and understand their queries/concerns

Table 6 (continued)

Main results	Theoretical implications	Practical implications
- The perceived value of VAs' recommendations strongly predicts customer engagement with the VAs (H11 supported)	- Confirmation of the positive association between perceived value and consumer engagement in a novel context, in this case, VAs - Adapting a measurement of consumer behavioural engagement to the context of VAs by employing three dimensions: intention to recommend the VA, intention to continue to use the VA and intention to follow the recommendations of the VA	- Practitioners should take into account the previously identified actions to maximise the perceived value of VAs' recommendations, which is crucial for increasing engagement. In the present study, perceived value predicted 75.8% of consumer–VA engagement

perceived intelligence of the assistant [e.g. mechanical, thinking, and feeling (Huang and Rust 2021)] and examine the effects of perceived degree of intelligence on the generation of perceived value and engagement. Third, we believe that some consumers enjoy their interactions with their VAs, which may be important for generating perceived value and consumer engagement (McLean et al. 2021). Thus, future research should extend the model to examine the effects of hedonic benefits (e.g. enjoyment) in the value generation process.

In addition, disruptive innovations, such as VAs, are perceived in various ways by different consumers, based on the consumers' capacities to deal with the innovation/ disruption (Belanche et al. 2020). Thus, future research should investigate the influence of consumers' characteristics (e.g. technology readiness, personality traits) on the cost–benefit analysis and perceived value of VAs' recommendations. Innovative technologies can trigger positive or negative feelings, based on their users' levels of technology readiness, comfort and use (Parasuraman 2000). For example, consumers' technology readiness has been positively linked with their perceptions of the convenience of a specific e-service (Lin et al. 2007). Similarly, technology readiness can reflect the degree to which consumers are efficient in using technologies (Belanche et al. 2020). Consumers with high technology readiness are more likely to be able to deal with the inconvenience that arises with new technologies, such as intrusiveness (Van Doorn et al. 2017), which may reduce its negative influence on perceived value. In addition, individual personality traits may also be crucial in terms of the individual's perceptions of innovative technologies (Belanche et al. 2020). For instance, previous research has indicated that extroverted persons interact more smoothly and conveniently with automated agents. Other personality traits (e.g. openness, conscientiousness, agreeableness, neuroticism; [Belanche et al. 2020]) might also influence how consumers interact with AI-based technologies.

Regarding the methodology employed, the data were collected from regular VA users in the USA. As the development of new technology services and the maturity of markets differ by country and culture, future research might examine other nations and cultures with different levels of technological development to enhance the generalisation of the model and findings. Furthermore, this study examines the perceived value of VAs' recommendations, but does not differentiate between types of assistants. Future research might compare consumers' experiences with smartphone-based VAs, such as Siri and Google Assistant, and their experiences with in-home VAs, such as Alexa and Google Home. The recommendations made by different types of VAs may create different levels of perceived value and consumer-VA engagement. Moreover, the study examines engagement from the perspective of consumer intentions. Whilst intentions have been shown to be a reliable indicator of actual behaviours (e.g. Venkatesh and Davis 2000), it might be fruitful to examine actual behavioural data and to conduct the analysis longitudinally, to gain a deeper understanding of consumer engagement with VAs.

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Declarations

Conflict of interest None.

References

Baek T, Morimoto M (2012) Stay away from me. J Advert 41(1):59–76

Balakrishnan J, Dwivedi YK, Hughes L, Boy F (2021) Enablers and inhibitors of AI-powered voice assistants: a dual-factor approach by integrating the status quo bias and technology acceptance model. Inf Syst Front 23(4):1–22

Barge S, Gehlbach H (2012) Using the theory of satisficing to evaluate the quality of survey data. Res High Educ 53(2):182–200

Becker JM, Klein K, Wetzels M (2012) Hierarchical latent variable models in PLS-SEM: guidelines for using reflective-formative type models. Long Range Plan 45(5–6):359–394

Belanche D, Casaló LV, Flavián C, Schepers J (2020) Service robot implementation: a theoretical framework and research agenda. Serv Ind J 40(3–4):203–225

Benlian A, Klumpe J, Hinz O (2020) Mitigating the intrusive effects of smart home assistants by using anthropomorphic design features: a multimethod investigation. Inf Syst J 30(6):1010–1042

Berry L, Seiders K, Grewal D (2002) Understanding service convenience. J Mark 66(3):1–17

Bhattacherjee A (2001) Understanding information systems continuance: an expectation-confirmation model. MIS Q 25:351–370

Brodie RJ, Hollebeek LD, Jurić B, Ilić A (2011) Customer engagement: conceptual domain, fundamental propositions, and implications for research. J Serv Res 14(3):252–271

Cabibihan J, Joshi D, Srinivasa YM, Chan MA, Muruganantham A (2014) Illusory sense of human touch from a warm and soft artificial hand. IEEE Trans Neural Syst Rehabil Eng 23(3):517–527

Casaló LV, Flavián C, Ibáñez-Sánchez S (2017) Antecedents of consumer intention to follow and recommend an Instagram account. Online Inf Rev 53(2):182–200

Cerekovic A, Aran O, Gatica-Perez D (2017) Rapport with virtual agents: what do human social cues and personality explain? IEEE Trans Affect Comput 8(3):382–395

Chattaraman V, Kwon WS, Gilbert JE, Ross K (2019) Should AI-Based, conversational digital assistants employ social-or task-oriented interaction style? A task-competency and reciprocity perspective for older adults. Comput Hum Behav 90:315–330

Chen ZF, Hong C, Li C (2017) The joint effect of association-based corporate posting strategy and eWOM comment valence on social media. Internet Res 13(4):9–38

Cheshin A, Amit A, Van Kleef GA (2018) The interpersonal effects of emotion intensity in customer service: perceived appropriateness and authenticity of attendants' emotional displays shape customer trust and satisfaction. Organ Behav Hum Decis Process 144:97–111

Cheung MY, Luo C, Sia C, Chen H (2009) Credibility of electronic word-of-mouth: informational and normative determinants of on-line consumer recommendations. Int J Electron Commer 13(4):9–38

Cheung CM, Shen XL, Lee ZW, Chan TK (2015) Promoting sales of online games through customer engagement. Electron Commer Res Appl 14(4):241–250
Chin WW (1998) Commentary: issues and opinion on structural equation modeling. MIS Q 22:7–16
Christophel DM (1990) The relationships among teacher immediacy behaviors, student motivation, and learning. Commun Educ 39(4):323–340
Cowan B R, Pantidi N, Coyle D, Morrissey K, Clarke P, Al-Shehri S, et al. (2017) " What can I help you with?" infrequent users' experiences of intelligent personal assistants. In Proceedings of the 19th international conference on human-computer interaction with mobile devices and services, pp 1–12.
Dabholkar PA, Bagozzi RP (2002) An attitudinal model of technology-based self-service: moderating effects of consumer traits and situational factors. J Acad Mark Sci 30(3):184–201
Davis FD (1989) Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q 13:319–340
De Barcelo Silva, Gomes MM, Da Costa CA, Da Rosa R, Barbosa JLV, Pessin G et al (2020) Intelligent personal assistants: a systematic literature review. Exp Syst Appl 147:113193
Flavián C, Casaló LV (2021) Artificial intelligence in services: current trends, benefits and challenges. Serv Ind J 41(14):853–859
Flavián C, Ibáñez-Sánchez S, Orús C (2020) Impacts of technological embodiment through virtual reality on potential guests' emotions and engagement. J Hosp Market Manag 30(1):1–20
Forgas-Coll S, Huertas-Garcia R, Andriella A, Alenyà G (2022) The effects of gender and personality of robot assistants on customers' acceptance of their service. Serv Bus 16:1–31
Fornell C, Larcker F (1981) Evaluating structural equation models with unobservable variables and measurement error. J Mark Res 18(1):39–50
Garvey AM, Kim T, Duhachek A (2022) Bad news? Send an AI good news? Send a human. J Mark 87(1):10–25
Georgiev D (2022) 2022's voice search statistics—is voice search growing?. In: Review 42. https://review42.com/resources/voice-search-stats/. Accessed 12 June 2022.
Goodhue DL, Thompson RL (1995) Task-technology fit and individual performance. MIS Q 19(2):213–236
Grover T, Rowan K, Suh J, McDuff D, Czerwinski M (2020) Design and evaluation of intelligent agent prototypes for assistance with focus and productivity at work. In Proceedings of the 25th international conference on intelligent user interfaces, pp 390–400.
Hagel J, Rayport JF (1996) Understanding your shoppers. Progress Groc 75(5):123
Hair JF, Ringle CM, Sarstedt M (2011) PLS-SEM: Indeed a silver bullet. J Mark Theor Pract 19(2):139–152
Hamet P, Tremblay J (2017) Artificial intelligence in medicine. Metabolism 69:S36–S40
Heninger WG, Dennis AR, Hilmer KM (2006) Research note: Individual cognition and dual-task interference in group support systems. Inf Syst Res 17(4):415–424
Henseler J, Ringle CM, Sinkovics RR (2009) The use of partial least squares path modeling in international marketing. New Chall Int Mark 20:277–319
Hernandez-Ortega B, Ferreira I (2021) How smart experiences build service loyalty: the importance of consumer love for smart voice assistants. Psychol Mark 38(7):1122–1139
Ho SY, Bodoff D (2014) The effects of web personalization on user attitude and behavior. MIS Q 38(2):497-A10
Hollebeek L (2011) Exploring customer brand engagement: definition and themes. J Strateg Mark 19(7):555–573
Hollebeek LD, Glynn MS, Brodie RJ (2014) Consumer brand engagement in social media: conceptualization, scale development and validation. J Interact Mark 28(2):149–165
Hsu CL, Lin JCC (2016) An empirical examination of consumer adoption of internet of things services: network externalities and concern for information privacy perspectives. Comput Hum Behav 62:516–527
Huang TL (2018) Creating a commercially compelling smart service encounter. Serv Bus 12(2):357–377
Huang MH, Rust RT (2021) Engaged to a robot? The role of AI in service. J Serv Res 24(1):30–41
Jehn KA, Shah PP (1997) Interpersonal relationships and task performance: an examination of mediation processes in friendship and acquaintance groups. J Pers Soc Psychol 72(4):775–790
Jeon HM, Sung HJ, Kim HY (2020) Customers' acceptance intention of self-service technology of restaurant industry: expanding UTAUT with perceived risk and innovativeness. Serv Bus 14(4):533–551
Kahneman D, Tversky A (1979) On the interpretation of intuitive probability: a reply to Jonathan Cohen. Cognition 7(4):409–411

Kim S, Choudhury A (2021) Exploring older adults' perception and use of smart speaker-based voice assistants: a longitudinal study. Comput Hum Behav 124:106914
Kim S, McGill AL (2011) Gaming with Mr. Slot or gaming the slot machine? Power anthropomorphism, and risk perception. J Consum Res 38(1):94–107
Klaus P, Zaichkowsky J (2020) AI voice bots: a services marketing research agenda. J Serv Mark 34(3):389–398
Kleijnen M, De Ruyter K, Wetzels M (2007) An assessment of value creation in mobile service delivery and the moderating role of time consciousness. J Retail 83(1):33–46
Komiak SY, Benbasat I (2006) The effects of personalization and familiarity on trust and adoption of recommendation agents. MIS Q 30(4):941–960
Lau CK, Chui CFR, Au N (2019) Examination of the adoption of augmented reality: a VAM approach. Asia Pac J Tour Res 24(10):1005–1020
Lee SM, Lee D (2020) Healthcare wearable devices: an analysis of key factors for continuous use intention. Serv Bus 14(4):503–531
Lee J, Kim S, Ki S, Park J, Sohn K (2019) Context-aware emotion recognition networks. In Proceedings of the IEEE/CVF international conference on computer vision, pp 10143–10152.
Li H, Edwards SM, Lee JH (2002) Measuring the intrusiveness of advertisements: scale development and validation. J Advert 31(2):37–47
Liébana-Cabanillas F, Muñoz-Leiva F, Sánchez-Fernández J (2018) A global approach to the analysis of user behavior in mobile payment systems in the new electronic environment. Serv Bus 12(1):25–64
Lin KY, Lu HP (2015) Predicting mobile social network acceptance based on mobile value and social influence. Internet Res 25(1):107–130
Lin CH, Shih HY, Sher PJ (2007) Integrating technology readiness into technology acceptance: the TRAM model. Psychol Mark 24(7):641–657
Lin YT, Doong HS, Eisingerich AB (2021) Avatar design of virtual salespeople: mitigation of recommendation conflicts. J Serv Res 24(1):141–159
Liu F, Zhao X, Chau PY, Tang Q (2015) Roles of perceived value and individual differences in the acceptance of mobile coupon applications. Internet Res 25(3):471–495
Loureiro SMC, Japutra A, Molinillo S, Bilro RG (2021) Stand by me: analyzing the tourist–intelligent voice assistant relationship quality. Int J Contemp Hosp Manag 33(11):3840–3859
Lynch JG Jr, Ariely D (2000) Wine online: search costs affect competition on price, quality, and distribution. Mark Sci 19(1):83–103
MacGeorge EL, Feng B, Guntzviller LM (2016) Advice: expanding the communication paradigm. Commun Yearb 40:239–270
Manikonda L, Deotale A, Kambhampati S (2018) What's up with privacy? User preferences and privacy concerns in intelligent personal assistants. In Proceedings of the 2018 AAAI/ACM conference on AI, ethics, and society 5(1): 229–235.
McLean G, Osei-Frimpong K, Barhorst J (2021) Alexa, do voice assistants influence consumer brand engagement?–Examining the role of AI powered voice assistants in influencing consumer brand engagement. J Bus Res 124:312–328
Mishra A, Shukla A, Sharma SK (2022) Psychological determinants of users' adoption and word-of-mouth recommendations of smart voice assistants. Int J Inf Manag 67:102413
Moon Y (2000) Intimate exchanges: using computers to elicit self-disclosure from consumers. J Consum Res 26(4):323–339
Moriuchi E (2019) Okay, Google!: an empirical study on voice assistants on consumer engagement and loyalty. Psychol Mark 36(5):489–501
Pal D, Babakerkhell MD, Zhang X (2021) Exploring the determinants of users' continuance usage intention of smart voice assistants. IEEE Access 9:162259–162275
Parasuraman A (2000) Technology readiness index (TRI) a multiple-item scale to measure readiness to embrace new technologies. J Serv Res 2(4):307–320
Park E, Ohm J (2014) Factors influencing users' employment of mobile map services. Telematics Inform 31(2):253–265
Park J, Son H, Lee J, Choi J (2018) Driving assistant companion with voice interface using long short-term memory networks. IEEE Trans Industr Inf 15(1):582–590
Phua J, Lin JSE, Lim DJ (2018) Understanding consumer engagement with celebrity-endorsed E-cigarette advertising on instagram. Comput Hum Behav 84:93–102
Podsakoff NP (2003) Common method biases in behavioural research: a critical review of the literature and recommended remedies. J Appl Psychol 88(5):879–903

Qiu L, Benbasat I (2009) Evaluating anthropomorphic product recommendation agents: a social relationship perspective to designing information systems. J Manag Inf Syst 25(4):145–182

Rauschnabel PA, Brem A, Ivens BS (2015) Who will buy smart glasses? Empirical results of two pre-market-entry studies on the role of personality in individual awareness and intended adoption of google glass wearables. Comput Hum Behav 49:635–647

Reeves B, Nass C (1996) The media equation: How people treat computers, television, and new media like real people and places. Cambridge University Press, UK

Rhee CE, Choi J (2020) Effects of personalization and social role in voice shopping: an experimental study on product recommendation by a conversational voice agent. Comput Hum Behav 109:106359

Ringle CM, Wende S, Becker JM (2015) SmartPLS 3. SmartPLS GmbH, Boenningstedt. J Serv Sci Manag 10(3):32–49

Rosenthal-von der Pütten A M, Straßmann C, and Krämer N C (2016, September) Robots or agents–neither helps you more or less during second language acquisition. In International conference on intelligent virtual agents, pp 256–268.

Rzepka, C., Berger, B., & Hess, T. (2020). Why another customer channel? Consumers' perceived benefits and costs of voice commerce. In Proceedings of the 53rd Hawaii International Conference on System Sciences, pp 4079–4088.

Sarstedt M, Hair JF Jr, Cheah JH, Becker JM, Ringle CM (2019) How to specify, estimate, and validate higher-order constructs in PLS-SEM. Austr Mark J (AMJ) 27(3):197–211

Schmidtz D (2006) The elements of justice. Cambridge University Press, UK

Short J, Williams E, Christie B (1976) The social psychology of telecommunications. Wiley, Hoboken

So KKF, King C, Sparks B (2014) Customer engagement with tourism brands: Scale development and validation. J Hospitality Tour Res 38(3):304–329

Sun Y, Guo Y, Zhao Y (2020) Understanding the determinants of learner engagement in MOOCs: an adaptive structuration perspective. Comput Educ 157:103963

Tan WK, Liao PH (2021) What triggers usage of gift-giving apps? A comparison between users and non-users. Serv Bus 15(3):515–538

Thien LM (2020) Assessing a second-order quality of school life construct using partial least squares structural equation modelling approach. Int J Res Method Educ 43(3):243–256

Ukpabi DC, Karjaluoto H (2017) Consumers' acceptance of information and communications technology in tourism: a review. Telematics Inform 34(5):618–644

Van Doorn J, Lemon KN, Mittal V, Nass S, Pick D, Pirner P, Verhoef PC (2010) Customer engagement behavior: theoretical foundations and research directions. J Serv Res 13(3):253–266

Van Doorn JJ, Mende M, Noble SM, Hulland J, Ostrom AL, Grewal D, Petersen JA (2017) Domo arigato Mr. Roboto: emergence of automated social presence in organizational frontlines and customers' service experiences. J Serv Res 20(1):43–58

Venkatesh V, Davis FD (2000) A theoretical extension of the technology acceptance model: four longitudinal field studies. Manag Sci 46(2):186–204

Verhagen T, Van Nes J, Feldberg F, Van Dolen W (2014) Virtual customer service agents: using social presence and personalization to shape online service encounters. J Comput-Mediat Commun 19(3):529–545

Vimalkumar M, Sharma SK, Singh JB, Dwivedi YK (2021) 'Okay google, what about my privacy?': User's privacy perceptions and acceptance of voice based digital assistants. Comput Hum Behav 120:106763

Wang LC, Baker J, Wagner JA, Wakefield K (2007) Can a retail web site be social? J Mark 71(3):143–157

Wang J, Yang Y, Wang T, Sherratt RS, Zhang J (2020) Big data service architecture: a survey. J Internet Technol 21(2):393–405

Whang C, Im H (2021) " I like your suggestion!" the role of humanlikeness and parasocial relationship on the website versus voice shopper's perception of recommendations. Psychol Mark 38(4):581–595

Whitford AB, Yates J, Burchfield A, Anastasopoulos JL, Anderson DM (2020) The adoption of robotics by government agencies: evidence from crime labs. Public Adm Rev 80(6):976–988

Zeithaml VA (1988) Consumer perceptions of price, quality and value: a means-end model and synthesis of evidence. J Mark 52(3):2–22

Zeithaml VA, Verleye K, Hatak I, Koller M, Zauner A (2020) Three decades of customer value research: paradigmatic roots and future research avenues. J Serv Res 23(4):409–432

Zhao X, Lynch JG Jr, Chen Q (2010) Reconsidering Baron and Kenny: myths and truths about mediation analysis. J Consum Res 37(2):197–206

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