How do interactive voice assistants build brands' loyalty?

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ABSTRACT

Voice assistants have emerged as a new form of technology that can identify human speech and respond accordingly via synthesized voices and this family of technologies has helped people accomplish various requirements in their daily lives. However, despite the numerous benefits of AI-based assistants, consumers' concerns about their privacy have increased. Nevertheless, only a few studies focus on the brand loyalty of customers, which influences the intention of consumers to persist in using voice assistants. Furthermore, the impact of brand credibility on the overall perceived value receives little attention. Therefore, this study attempted to identify the mechanism through which the users of voice assistants might develop reuse intention and loyalty toward a specific service provider brand and analyze how brand credibility can influence the overall perceived value of voice assistants. The study drew on the uses and gratification theory, signaling theory, and prospect theory to develop the conceptual model and its underlying hypotheses. Using purposive sampling and an online survey, data were collected from 426 Chinese users of AliGenie, Alibaba's intelligent personal assistant. Data and the hypothesized model were analyzed using partial least squares structural equation modelling. Findings from quantitative analysis identified the perceived privacy risk as the most significant factor and obstacle influencing consumers' overall perceived value toward the usage of voice assistants. Furthermore, findings indicate that brand credibility moderates the existing relationship between the perceived privacy risk and the overall perceived value, a high brand credibility results in a much lower association between the perceived privacy risk and overall perceived value. Furthermore, the findings discovered a significant and positive relationship between brand loyalty and individuals' continued usage of voice assistants.

KEYWORDS:
Brand loyalty, Perceived privacy risk, Brand credibility, Perceived value, Voice Assistants

1. Introduction

As consumers are now gravitating toward omnichannel purchasing, technologies like artificial intelligence (AI) have become a source of assistance (Balakrishnan and Dwivedi, 2021). Voice assistants (VAs) are a sort of AI that is currently being developed in the market, and they have progressively earned their position in terms of information gath-ering (Jain et al., 2022). According to Moriuchi (2019), the efficacy of exchanging information via speech exceeds that of textbased commu-nication. Companies such as Microsoft, Google, Amazon, Xiaomi, Ali-baba, and Facebook aim to frequently communicate with customers using the speech recognition system currently available in the market (Platz, 2017). VAs have altered the manner in which people consume knowledge resources, engage in activities, seek information, purchase items, and connect with businesses (Jain et al., 2022). Voice search is now utilized by 27 % of the global internet population, and according to McCue (2018), in-home VAs is anticipated to grow by 1000 % between 2018 and 2023. Consequently, experts believe virtual assistants will eventually replace existing technologies like personal and laptop com-puters for many basic retail tasks (e.g., Gartner, 2016).

Currently, AI-driven VAs are regarded as the most disruptive and revolutionary innovations introduced to the consumer electronic market. Making their way into individual lives aggressively, VAs are redefining how consumers perform their daily tasks, making them faster and smarter in their day-to-day decision-making (Hasan et al., 2021; Vimalkumar et al., 2021). With the help of VAs, people may now operate computers and make choices simply by using voice input. This voice-enabled feature enables users to accomplish tasks more conveniently and entertainingly. According to Amazon, the rapidly expanding presence of virtual assistants is primed to become the next great upheaval in the field of human-computer interaction (Kaplan, 2018). Access to information is the most significant benefit provided by VAs, making consumers eager to incorporate the technology into their daily lives. This demand is an opportunity for businesses to incorporate technology into their marketing approach. While many studies agree that the use of VAs is limited to basic functions like search, alarms, weather, and music (Mari, 2019), voice commerce is on the increase, with revenue hitting $1.8 billion in 2018 and projected to attain $40 billion by 2022 in the United States alone (Hayllar and Coode, 2018).

Several studies have been conducted on the intention of users to adopt voice assistants in their daily lives. This technology has been investigated from various perspectives, such as social benefits, trust in technology, features of voice assistants, and ease of use (Fernandes and Oliveira, 2021; Hoy, 2018; McLean and Osei-Frimpong, 2019; Mishra et al., 2021). Many studies have examined the perceived privacy risks of VA. Consumers have debated the security and privacy concerns posed by digital VAs (Cao et al., 2022). These increasing concerns stem from how information is obtained and utilized by these cutting-edge technologies (Dubiel et al., 2018). Similarly, Martin (2018) highlighted that user of VAs view privacy risk as a secondary usage of information that decreases the trust in a website. Moreover, Dinev and Hart (2006) also stated that higher levels of perceived privacy risk result in lower willingness and trust in digital technologies. Therefore, the perceived privacy risk remains crucial for customers' adoption of VAs and other automated technologies (Fernandes and Oliveira, 2021).

In addition, customers' brand loyalty is another important aspect of the continued usage of voice assistants by consumers. Notably, brand loyalty denotes consumers' inclination to prefer a specific brand over the competing brands regardless of price discrepancies. Nasir (2005) indicated that customers' brand loyalty is essential in competitive marketplaces as it allows companies to form robust relations, gain market share, and attain maintainable competitive advantages. Hernandez- Ortega and Ferreira (2021) also introduced brand loyalty as the primary source of continued development and revenue. They explained that loyal customers would be more likely to pay higher costs and tend to be more understanding of difficulties during the in-service performance readier to recommend smart voice assistants to others. Accordingly, brand loyalty is critical for VA service providers since the repeated use of these technologies is generally free of charge, and brand loyalty resulting from the memorable, effective, and efficient interactions with the voice assistant becomes an indispensable strategic goal of VA service providers. Most technology giants and industry leaders usually endure massive financial burdens developing and maintaining their VA services to benefit from brand loyalty as an invaluable strategic gain (Hasan et al., 2021). Therefore, the analysis of brand loyalty and the variables influencing it become crucial to digital assistants.

Brand credibility is another significant concern of VAs. Besides a device fulfilling the social and psychological requirements of the consumer, it is still essential for that device to represent a credible picture of the product's value and trustworthiness (Hasan et al., 2021). Moreover, brand credibility is generally outlined as comprising two major components: trustworthiness and expertise (Erdem and Swait, 1998). Cuong (2020) highlighted brand credibility as having a substantial positive impact on consumer satisfaction, perceived value, and purchase intention. Jain et al. (2022) also highlighted that brand credibility improves consumers' social comfort and perceived value. Additionally, credible brands can minimize risks and thus improve the assessment of consumers (Baek, 2007). However, the impact of brand credibility on how VAs are valued also receives little attention in the literature.

Given these issues, the study aims to identify the mechanism through which users of voice assistants might develop reuse intention and loyalty toward a specific service provider. Subsequently, the impact of brand credibility on dimensions' attractiveness, trustworthiness, and expertise on brand loyalty was examined. The study also analyzed how brand credibility may influence consumers' overall perceived value of voice assistants. To obtain a deeper understanding of voice interactions, this research incorporates the uses & gratification theory (U&GT) (McLean and Osei-Frimpong, 2019) to reveal how consumers from different experiences and interests regard VAs features (utility, hedonic and social). The signaling theory has been employed to describe how brands influence consumer purchase behavior when its consumers are unsure of the quality of their purchase and the way it affects their decisions, which subsequently reduces consumers' decision risks by reducing the uncertainty associated with the use of VAs (Akdeniz et al., 2013). Prospect Theory (Kahneman and Tversky, 1979) has been employed to justify how consumers perceive future potential gains concerning the (overall) voice assistant value that makes them willing to trade off privacy threats for using voice assistants.

The manuscript is organized as follows: Section 2 presents the literature alongside the hypotheses and research models, Section 3 presents the research methodology of the study, Section 4 highlights the analysis and results, Section 5 features the discussions and implications for theory and practice, Section 6 highlights the limitations and future directions for research, and Section 7 concludes the study.

2. Literature review and research hypotheses

2.1. Current studies relating to the adoption of voice assistants

Sophisticated technologies such as VAs have endowed consumers with several choices. In addition to convenient interactions with technology through the use of voice (Alepis and Patsakis, 2017), the existence of VAs has also resulted in various unforeseen expectations in areas of users' emotional satisfaction (Castelo et al., 2019). Although the use of VAs in shopping is relatively new, there are several studies that report the disruptive potential and expected growth of the practice (Kumar et al., 2020; Rzepka, 2019). Nasirian et al. (2017) investigated the factors impacting consumers' adoption of VAs and identified the quality of interaction as a significant driver of trust that influences their intention to use it. Sun et al. (2019) examined data from Alibaba's VAs, "TMall Genie", and discovered that the VAs increased purchase levels and customer engagement. Based on the study on the perspective of "uses and gratification" undertaken by Lee and Cho (2020), this study attempts to ascertain users' motives for using smart speakers and examine the relationship between these motives and the effectiveness of smart speaker advertising.

Natural language processing technologies have developed rapidly in recent years, enabling the development of various voice-assistant devices for consumer use (Shalini et al., 2019). Virtual assistants powered by artificial intelligence, such as Amazon's Alexa, Google Assistant, and Apple's Siri, which respond to natural language and replicate human communication, have become increasingly popular (Hoy, 2018). These technologies assist users in undertaking various daily tasks like searching for information, answering questions, recommending products, and managing personal schedules (Palanica et al., 2019). Liao et al. (2019) investigated the role of privacy and trust in adopting smart personal assistants via the expansion of technology acceptance frameworks. The findings reveal that concerns about privacy and trust in corporations' adherence to social contracts in connection to smart personal assistant data influence the usage of smart personal assistants. By deploying the prosocial relationship theory to consumer social relationships, Han and Yang (2018) investigated the interaction between customers and their smart assistants and their continuation intentions. Their research revealed that interpersonal attraction (task attraction, social attraction, and physical attractiveness) and privacy risk influence the use of smart personal assistants.

McLean and Osei-Frimpong (2019) analyzed the motivation for adopting and using in-home VAs by combining the U&GT alongside technology theories, and their results reveal that VAs equip individuals with utilitarian, symbolic, and social benefits in addition to hedonic benefits. However, hedonic benefits only motivate individuals to use voice assistants. Orehovaˇcki et al. (2019) examined the elements that contribute to the adoption of intelligent personal assistants (IPAs). Two higher education institutions participated in the study, with IPAs from Google Assistant serving as the representative sample. Finally, based on the findings of the literature analysis, an evaluation framework comprising eight constructs was established (Effectiveness, Controllability, Reliability, Accuracy, Ease of Use, Usefulness, Satisfaction, and Loyalty). IPA users were observed to be willing to adopt the software if they found it beneficial and were satisfied with it.

Siddike and Kohda (2018) highlighted reliability, attractiveness, and emotional attachments as the various factors that motivate trustworthy attitudes toward cognitive assistants (CAs). They further explained that innovativeness influenced the intention to indulge in the use of CAs. A research team led by Nasirian et al. (2017) examined the potential factors affecting the acceptance and use of voice assistants. They concluded that the quality of interaction was an important factor influencing individuals' trust and adoption of this technology. Moriuchi (2019) examined how consumer engagement with VAs was influenced by the comprehended ease of use and usefulness of technology and its influence on consumer loyalty. They also explored the moderating role of localization on voice assistants in online-based transactional and non- transactional activities. Furthermore, they discovered that perceived simplicity of use and usefulness influenced voice assistant user engagement and loyalty. Chi et al. (2020) addressed how customers' acceptance of their use of artificially intelligent devices in service encounters could be explained from a theoretical model of AI device acceptance. From prior studies, six predictors related to the use of AI devices in service encounters have been identified namely social influence, hedonic motivation, anthropomorphism, performance expectancy, effort expectancy, and emotion. Research reveals performance expectancy as positively related to social influence and hedonic motivation, and effort expectancy as positively related to anthropomorphism. Effort expectation and performance both remain significant antecedents of customer emotions, thus helping to determine the acceptance of AI devices by customers.

Buteau and Lee (2021) highlighted three factors for predicting the time and manner in which people will use voice assistants such as Alexa and Siri. According to the research, exhibited attitudes toward the utilization of voice assistants were observed to be positively associated with perceived usefulness, personal norms, and perceived security. Furthermore, privacy concerns correlate negatively with exhibited attitudes toward the use of voice assistants, which in turn, correlate positively with behavioral intentions. Song (2019) investigated the elements influencing the decision of people to adopt and use an artificial intelligence virtual assistant. The technology adoption model confirms that the comprehended usefulness and ease of use both positively affect the tendency to adopt and use an AI virtual assistant. Hasan et al. (2021) developed a model to analyze consumer trust, interaction, perceived risk, and the novelty value of AI-supported devices in a bid to determine their influence on brand loyalty. Findings reveal that perceived risk has a significantly negative effect on brand loyalty, with other factors significantly boosting brand loyalty. The novelty value of utilizing Siri is moderated by brand involvement and customer innovativeness, with the novelty value being higher for people who were more innovative and less involved with the brand. A study by Jain et al. (2022) revealed brand credibility considerably moderates the link between the features and the perceived value of VAs, and that a high level of brand credibility minimizes users' perception of privacy issues.

Vimalkumar et al. (2021) examined how consumers perceived privacy concerns and their effect on their adoption of voice-based digital assistants. Their study revealed that trust positively and significantly influences their adoption behavior. In this study, privacy risk did not directly influence adoption behavior but had a considerable impact on customers' trust and perception of privacy and signaled the full mediation of risk through trust and privacy concerns.

The research conducted by Belanche et al. (2019) provides insights on how a wide variety of potential customers adopted Robo-advisors. This study reveals that mass media and interpersonal norms and attitudes toward Robo-advisors were considered to be the major factors responsible for its adoption. Perceived usefulness and attitude were observed to be more influential for consumers who were more familiar with robots; subjective norms were more influential for customers from Anglo-Saxon countries and those having little experience with robots.

Fernandes and Oliveira (2021) demonstrated that digital voice assistants were only used in service encounters that were based on the drivers of adoption. Their research revealed that functional, social, and relational factors all play a role in adoption, impact crossover effects between them, and that experience and a need for human interaction moderated these effects. Despite the abundance of previous research on VA only a few studies examine how consumers perceive brand credibility in their establishment of trust in voice assistants, contributing to the total value of voice assistants. As a result, brand credibility greatly influences how people make decisions and use voice assistants. To fill this gap in the literature, the current study examined whether brand credibility affects the total value of voice assistants. Table 1 demonstrates users' adoption of digital voice assistants.

2.2. Underpinning theoretical frameworks

To gain a deeper understanding of voice interactions, this research incorporated the U&GT (McLean and Osei-Frimpong, 2019) with theories on technology for an insight into the motivation for the adoption and usage of VAs in the future. A signaling theory (Erdem and Swait, 1998) has been employed to justify how brands reshape consumers' buying behavior when they are unsure of the quality of their purchase. Furthermore, prospect theory (Levy, 1992) has received accolades for its theoretical assumption that individuals are risk-averse in terms of gains but risk-acceptant in terms of losses and for its focus on the reference point around which decisions are framed. Prospect theory has been deployed to explain the manner in which customers anticipate possible future advantages with respect to the (total) voice assistant value that spurs them to trade-off privacy threats for the use of voice assistants.

2.2.1. The uses & gratification theory

The U&GT is a psychological model of motivation (Katz et al., 1974) that can be used to gain an insight into the motivation of individuals toward the adoption of technology (Grellhesl and Punyanunt-Carter, 2012). The theory was enacted to justify the reliance of individuals on specific media and technology to satisfy their needs (Gallego et al., 2016). The Uses and Gratifications Theory of communication has recently been recognized as one of the most relevant theories (Madan and Kapoor, 2021). It hypothesizes that different characteristics are important to users in their choice of media (van der Wurff, 2011). U&GT has been termed an “axiomatic theory” by Luo and Remus (2014) since its principles were widely applied to a range of mediated communication, including traditional media and newspapers, alongside interactive media such as the Internet. Moreover, U&GT helps describe why and how customers confront distinctive forms of media to fulfill requirements and satisfy specific needs (Katz et al., 1973). This viewpoint is embedded in the opinion that customers actively look for several kinds of media, for certain purposes, instead of only inactively accepting them (Dolan et al., 2016). Therefore, U&GT concentrated on the gratification of consumers' particular demands to explain the mechanisms involved in choosing and employing voice assistants' technology. Thus, U&GT can be implemented to gain an insight into people's desire to use voice assistants, as they mostly satisfy a variety of needs. The U&GT model provides an interesting theoretical view through which a better understanding of the motivation behind the use of AI voice assistants (such as the Google Assistant and Amazon's Echo) could be derived. According to the theory, utility, hedonic and social presence features influence users' perception of voice assistants, subsequently revealing their behavioral intention toward its continuous use. This study has used the U&GT lens to demonstrate that utility features, hedonic features, and social presence features influence users' perception of voice assistants, ultimately leading to their behavioral intention to continue using the device and brand loyalty. Also, we employed U&GT to examine how attractiveness, trustworthiness, and expertise will facilitate bonding between consumers and brand loyalty.

In addition, since users are from different personality backgrounds (e.g., age and gender), their varying interests, and the perception of the utility, hedonic, and social benefits may be vastly different. It is also possible that there are significant differences in the usage and adoption of technology between men and women (Li et al., 2008). Therefore, based on U&GT, we suggest that age and gender will moderate the relationship between utility features, hedonic features, and social presence features and how they influence users' perception of voice assistants with the individual's perceived value. Utility features, hedonic features, social presence, perceived value, voice assistant continued usage intention, and brand loyalty are constructs that correspond to U&GT in the present study.

Table 1
Users' adoption of digital voice assistants.

Study	Context	Method	Key findings
McLean and Osei-Frimpong (2019)	Home voice assistants	Survey with a sample of 724 users	The results show that users are motivated by the social, utilitarian, and symbolic benefits provided by voice assistants.
Jain et al. (2022)	Voice assistants	Both empirical and qualitative methods	Brand credibility significantly moderates the relationship between voice assistants' features and the overall perceived value of voice assistants. Moreover, they found that higher brand credibility decreases customers' perception of privacy risks.
Fernandes and Oliveira (2021)	Digital voice assistants	Survey with 238 young consumers	Results demonstrate that functional, social, and relational factors impact digital voice assistants' adoption. Moreover, they found that User experience and preference for human interactions play a moderating role.
Mishra et al. (2021)	Smart Voice Assistants	Survey of 360 respondents	Results demonstrate that playfulness and escapism positively impact hedonic attitudes. Additionally, the utilitarian attitude has a significant influence on smart voice assistants' usage and word-of-mouth recommendations. In contrast, social presence, visual appeal, and anthropomorphism define utilitarian attitudes.
Cao et al. (2022)	Smart voice assistants	A survey of 255 UK Airbnb guests	The consequences demonstrate that perceived emotional value, privacy risk, and perceived functional value had a significant impact on the intention of Airbnb guests for adopting smart voice assistants. On the other hand, the impact of perceived social value for smart voice assistants' adoption was not significant.
Dubiel et al. (2018)	Virtual Personal Assistants	Survey on 118 virtual personal assistants' users	The consequences reveal that, in comparison to infrequent users, frequent users of virtual personal assistants are more pleased with their virtual assistants. Furthermore, they found that frequent users of virtual assistants are keener to use technology in a variety of settings. But both users have equal concerns regarding the privacy of technology.
Hasan et al. (2021)	Voice assistants, like Siri	Survey from 675 Apple iPhone-users	The results indicated that perceived risk has a significant negative impact on brand loyalty; nevertheless, trust, interactions, and novelty value have a significant and positive influence on brand loyalty. Moreover, brand involvement moderates the relation between the novelty value of Siri and consumer innovativeness.
Patrizi et al. (2021)	Voice assistants	Quantitative exploratory from 337 respondents	The exploratory factor analysis demonstrates an acceptable structure with four dimensions symbolic benefits, hedonic benefits, utilitarian benefits, and human-like voice.
Vimalkumar et al. (2021)	Voice-based digital assistants	A quantitative survey from 252 Indian users.	The results revealed that perceived privacy risk does not impact consumers' intention to adopt voice-based digital assistants. They also found that performance expectancy moderates the relationship between privacy concerns and intention to adopt voice assistants.
Moussawi et al. (2021)	Personal intelligent agents	Online experiment from 271 college students in the US	The results from an online investigation demonstrate that humor and voice positively and significantly impact users' opinions of anthropomorphism. These perceptions significantly influence users' emotion-based trust, which enhances their intention to use the intelligent personal agents.

2.2.2. Signaling theory

Brand credibility is explained by signaling theory (Erdem and Swait, 1998). A signaling theory is used to cushion the incertitude among stakeholders and assess the quality and value of brand offerings (Karanges et al., 2018). Brand credibility emerged from the signaling theory of marketing, which is largely driven by information economies in which companies use their brands to communicate messages to the public. Marketing strategies that target a specific brand send these signals. Branded products of high quality are often more highly perceived by consumers than unbranded ones, as they are accepted as true signals emitted by the brand over time. In this way, brands are now considered to have effective quality signs that are not observable (Rao et al., 1999).

Erdem and Swait (1998) stated that a brand is a credible signal since it represents a company's reputation and overall marketing strategies. Brand signals can thus be used to rapidly assess the quality of a product or service (Dawar and Parker, 1994). According to signaling theory, credibility plays an important role in a brand signal's ability to convey information effectively (Phlips, 1990). Conclusively, brand credibility is at the core of a brand as a signal (Erdem et al., 2002). Based on signaling theory, brand credibility is observed to control the link between customers' perceptions of voice assistants' functions and general worth, and hence, their willingness to continue using them. Moreover, signaling theory indicates that credibility is a significant factor in efficiently expressing information about the brand. Baek et al. (2010, p. 664) indicated that "the heart of brands as signals is brand credibility." Signaling theory can describe the significance of brand credibility and demonstrate exactly how brand credibility acts as a reliable signal and a measure to customers for evaluating the product and service quality. Especially for intelligent technologies such as voice assistants, brands can be perceived as signals that express the quality of a product and its reputation, reducing perceived risks and irritation. Therefore, we suggest that, based on signaling theory, brand credibility moderates the relationship between people's perceptions of the features and overall value of VAs and their behavioral intentions toward continuing to use VAs. Furthermore, people's perceptions of the risk and irritation of using VAs may also be different at low or high brand credibility levels. The study draws on signaling theory to incorporate brand credibility and its sub-constructs of attractiveness, trustworthiness, and expertise into the proposed conceptual model.

2.2.3. Prospect theory

Prospect theory, developed by Kahneman and Tversky (1979), argued that people overvalue certain outcomes compared to probable ones. This phenomenon was dubbed the "certainty effect" by Kahneman and Tversky (1979). They also noted that the certainty effect results in risk-aversion in selecting choices involving certain rewards, and risk- seeking in selecting choices involving certain losses. According to prospect theory, individuals tend to undervalue less probable outcomes compared to more probable ones, leading them to take risks when experiencing possible large losses or gains, and refrain from taking risks when posed with, perhaps, large gains or small losses. Following this, the risk is considered disproportionally, and a greater role is played in the decision-making process (Day et al., 2020).

As described in prospect theory, loss aversion is defined as the likelihood that people prefer avoiding losses instead of deriving gains. Consequently, people are averse to taking risks when evaluating a potential profit since they would rather avoid losses than make gains. Furthermore, people tend to do well when exposed to risks that may possibly mitigate a loss, referred to as risk-taking behavior. Prospect theory states that a risk-averse investor would sell a stock that gains money, while a risk-seeking investor would prefer to hold on to a stock that results in losses (Cao et al., 2010). Concerning the use of VAs and other intelligent technologies, customers may strike a balance between the advantages (brand inclusive) and the risk of a privacy compromise. With respect to prospect theory, it is proposed that users make trade-off judgments based on their sense of gain when examining the utility of voice assistants. Moreover, prospect theory demonstrates the decision- making behaviors of users in risk and uncertain circumstances. This theory also explains why users might make irrational or conflicting decisions (Khan et al., 2022). Remarkably, this can deliver a valuable vision of why users might decide to accept or reject digital voice assistants under conditions of risk along with giving a reason for the perceived irrational or conflicting decisions regarding the digital voice assistants' adoption. By drawing on prospect theory, we propose that consumers make decisions under the risk and irritation toward the perception of gain about the value of voice assistants. Thus, the study draws on prospect theory to consider perceived privacy risk and irritation as components of the proposed conceptual model.

2.3. The conceptual model and hypotheses

The present study draws on the uses & gratification theory, signaling theory, and prospect theory to develop the conceptual model and its underlying hypotheses. Fig. 1 demonstrates the conceptual model of this study. This figure highlights the constructs associated with each particular theory. Discussion regarding the hypotheses processed is provided in the following.

2.3.1. Utility features

According to consumer behavior studies, there are two basic dimensions for product and service consumption – the utilitarian and the hedonic (Babin et al., 1994). The utilitarian value has been described as a general evaluation (i.e., judgement) of functional advantages and losses. It is basically a task-specific procedure of online shopping, that is, the process of considering and assessing the product, service, and price features before purchase (Hoffman and Novak, 1996). Utility features involve purchasing a product by heuristics, implementing risk lessening approaches, and obtaining information through search strategies (Park et al., 2012). Utilitarian value has been underlined as a serious and genuine practice that accurately forms a customer's decisions and influences their perceived value. Utilitarian internet shoppers seek to emphasize the function of a certain objective, such as comparing the pricing of a product or service sequel to making a final purchase. Given the variety of utility functions available in voice assistants, there is a possibility of consumers' perceptions being influenced by the efficiency of these devices. As such, hypothesis H1:

H1. Utility features positively influences the perceived value of voice assistants.

2.3.2. Hedonic features

The intrinsic or hedonic value defines self-oriented facets related to entertainment, while the extrinsic (utilitarian) value explains goal- oriented elements; meanwhile, both values play significant roles in new technology habits. Regardless of whether a purchase occurs or not, the focus of hedonic features is mainly on fun, amusement, and other pleasing features of shopping (Moe, 2003). Ashfaq et al. (2021) described hedonic value as an enjoyable and gratifying perception peculiar to a particular technology or service. Hedonic value is one of the most important factors in customer perceived value. Hedonic buyers consider websites that offer not only secure transactions, confidentiality, privacy, cooperative interactions, and swift access to massive amounts of information but also intrinsic emotional value and aesthetics that enrich the desire to shop online (Overby and Lee, 2006). Past studies have revealed that hedonic features positively affect to loyalty and the perceived value of services rendered (Llach et al., 2013). In line with this, Park et al. (2012) claimed that the variety of options on the shopping website has a positive association with hedonic web browsing for clothing products. With regards to voice assistants, the satisfaction and pleasure derived from a new interactive practice would be vital to using such technology. Subsequently, the study proposes hypothesis H2:

H2. Hedonic features have a positive impact on the perceived value of voice assistants.

2.3.3. Social presence

Social presence can be described as the ability of communicators "to expressively portray themselves, socially and emotionally, as 'real' people (i.e., in their real self)" in facilitated communications (Garrison et al., 1999). According to Chang and Hsu (2016), social presence is vital in defining the concept of messages and will, therefore, impact social interactions among consumers. It has also been considered a behavioral involvement in which actions of users are inter-reliant, linked to, or reactive to the other (Cui et al., 2013). Osei-Frimpong and McLean (2018) applied the principle of the CASA pattern to study people's use of voice assistants and discovered that the social presence of voice assistants was an essential element defining its adoption by an individual. According to Moon (2000), social responses to computer-based devices are because people are placed from evolution; accordingly, social responses are enriched in the interaction involving

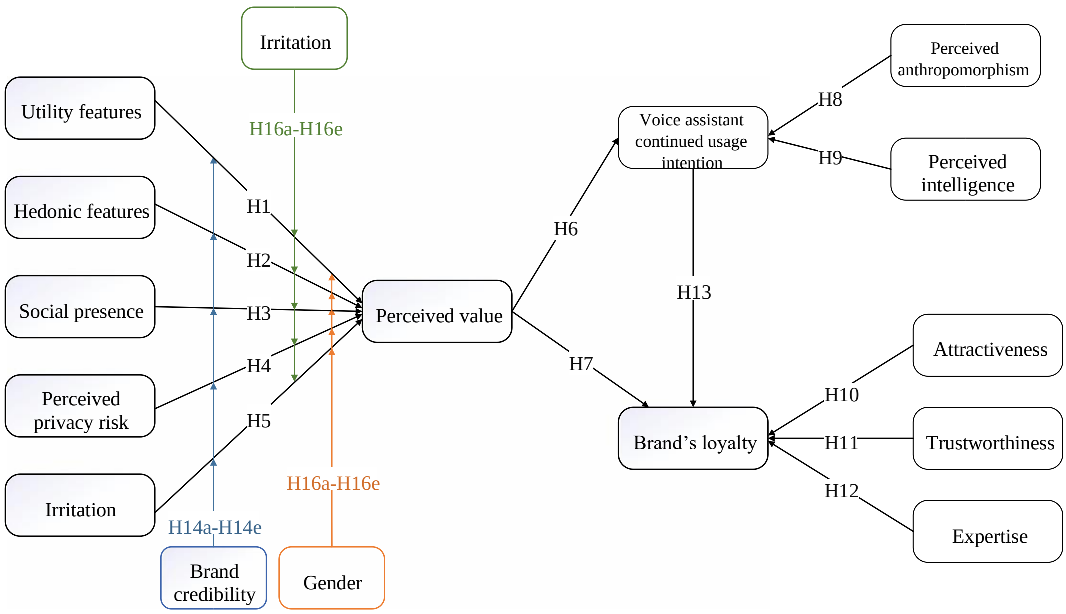


Fig. 1. The conceptual model of the study.

digital devices embracing human-like aspects. Moreover, an analysis of Amazon users' reviews advocated that a voice assistant is much more pleasing when the social aspects of voice assistants appeal to them (Purington et al., 2017). Therefore, it is correct to presume that the greater the degree of social presence felt by the user about the voice assistant, the richer the experience they derive when using those devices. As such, they become more likely to interact with voice assistants.

H3. Social presence positively influences the perceived value of voice assistants by individuals.

2.3.4. Perceived privacy risk

Perceived privacy risk can be defined as the fear of inappropriate use of consumer data and violation of their privacy by online companies (Nyshadham, 2000). One aspect of this risk could be the undisclosed capturing of consumers' shopping habits. In evaluating the adoption and use of information technology, perceptions of privacy risk and trust are critical. Therefore, they are both relevant to the decision to share sensitive personal information with others (Hasan et al., 2021). Considering that AI is a relatively new, emerging, and sophisticated technology, it is understandable that the average person may not fully understand how the technology operates, thereby putting the consumer in the precarious position of blindly trusting a company. People's perception of a privacy risk will result in them lowering their tendency to use voice assistants, which negatively influences their motivation to use the technology (McLean and Osei-Frimpong, 2019).

According to a recently conducted study on the usage of speech assistants, perceived privacy risks are important barriers to adopting the technology (Seiderer et al., 2020). Therefore, the perceived privacy risk can pose a major obstacle to people's use of AI voice assistant technology. However, customers may learn to live with their privacy concerns in favor of new technology over time as they become accustomed to using it. Consequently, the following hypothesis is proposed:

H4. The perceived privacy risk negatively influences an individual's perceived value of voice assistants.

2.3.5. Irritation

A consensus among scholars is that irritation is cogitated as an essential as well as robust dimension of U&GT (Liu et al., 2012). According to Morimoto and Chang (2006), irritation is the state of being negatively and unpleasantly affected by advertising stimuli. According to Teo et al. (2003), irritation is any undesirable effect that is contrary to the values upheld by a person. In line with these definitions, irritation can occur if ease of use is not provided. Irrespective of the type of website, irritation caused by unpleasant effects or loss of time while using a website is detrimental to users. For instance, an online shopping experience can be irritating to buyers. As Hasan (2016) highlighted, consumer irritation is due primarily to unpleasant experiences in the shopping environment. In their study, Florentha et al. (2012) claimed that higher levels of irritation were observed to be correlated with lower perceptions of the promotional value of a videocast. The Theory of Psychological Reactance holds that those who are perceived as being deprived of their freedom of choice tend to react negatively (Ünal et al., 2011). Thus, the degree of irritation is mainly determined by evaluators observing both verbal and nonverbal expressions of users' behaviors (Bruun et al., 2016). In light of previous research that highlighted a negative relationship between perceived value and irritation (Saadeghvaziri and Hosseini, 2011; Lin and Bautista, 2018), the following hypothesis is proposed:

H5. Irritation has a negative association on an individual's perceived value of voice assistants.

2.3.6. Perceived value and continued usage intention

Perceived values are descriptions of customers' desired and significant-end goals. In the case of post-adoption of IT services, the perceived value might be an important influencer of behavioral consequences such as the continued usage of applications (Malik and Rao, 2019). In many business sectors today, the focus of management is on the provision of the best possible value to its customers. A consumer's perceived value is based on a trade-off between their perceived benefits and perceived costs (Zeithaml, 1988). Such trade-off is the user's assessment of the "utility" perception of the benefit and worth of a product or service. According to Choi et al. (2018), firms can transform the perceived value of consumers in response to changes in the business environment, consumer needs, or competition: "(a) by offering a corresponding quality at a corresponding price, (b) by offering topnotch quality at a premium price, or (c) by offering low quality at a discounted price."

The perceived value can be assessed in four dimensions – emotional, social, quality and monetary values[1] (Putrianti and Semuel, 2018). Social value refers to the products that help improve the concept of self- social consumers, emotional value relates to the affirmative feeling resulting from the utilization of a product, quality value is the perceived quality and expected performance of a product, and monetary value is the utility received from products that reduce short-term and long-term costs. Prior studies have discovered a positive and significant relationship between the perceived value of products and the continued usage intention (Lavado-Nalvaiz et al., 2022; Hong et al., 2017). Chen and Chen (2010) argued that the perceived value was a more accurate predictor of continued usage intention (Han et al., 2013). Sharma and Klein (2020) reported that more consumers were inclined to engage in online group purchases should they perceive the value of engaging in such activities as high. As a result, a higher perceived value of technology will influence a consumer's choice of acceptance. Hence, hypothesis H6 is postulated as follows:

H6. Perceived value is positively related to the continued usage intention of voice assistants.

2.3.7. Perceived value and brand loyalty

In 1971, Jacoby predicted the first conceptual and complete characterization of brand loyalty. Brand loyalty, in his perspective, is defined as follows: "The one-sided (non-random) behavioral response (purchase) exhibited over time by some decision-making unit with regards to one or more alternative brands from a set of brands, and [it] is a function of psychological processes." Many scholars have projected brand loyalty to include several other characteristics besides the behavioral traits observed since the 1990s. They can be regarded as brand loyal customers if they exhibit a preference for a particular brand outside of the recurring purchase behavior.

The ultimate goal of a marketing team should be to retain existing customers, attract new ones, convert them to loyal and recurrent customers, and maintain and build on that loyalty (Tabaku and Kushi, 2013). As highlighted, both customers and service providers can benefit from customer loyalty. As described by Aaker (1996), brand loyalty permits the usage of price premium strategies by companies, as these tactics help increase cash flow. Since devoted customers patronize the brand regularly, they tend to spend more money on the same brand, not necessarily indicating a single product but also other products offered by the same company and its brand.

Previous research has discovered the direct relationship between the perceived value and consumers' brand loyalty to be consistent. For instance, several scholars contended that consumers' perceived value is tied to loyalty and positive referrals (Abu ELSamen, 2015; He et al., 2012; Lin et al., 2017). The following hypothesis is thereby proposed:

H7. Perceived value is positively related to the brand loyalty of voice assistants by individuals.

2.3.8. Perceived anthropomorphism and continued usage intention

Anthropomorphism is the adoption of human-like characteristics, motivations, beliefs, or emotions by non-human actors in real or imagined situations (Epley et al., 2007). A common instance of anthropomorphizing in robotics is the tendency of humans to perceive robots as human-like when presented with visual, auditory, or tactile stimuli (Zawieska et al., 2012). Artificial intelligence agents and customers interact more efficiently when service agents are anthropomorphized (De Visser et al., 2017). Anthropomorphism is a psychological concept that facilitates social interaction between humans and non-humans (Blut et al., 2021). Anthropology satisfies two essential human needs: the desire for social bonding and the desire to control and understand the environment. Past studies have revealed that people's perception of robots' anthropomorphism affects consumers' behavioral intentions (Han, 2021). The use of humanoid robots having a human voice-based communication system has been observed to significantly affect the trust and perception of users, which subsequently increases their intention to use the robot (Han, 2021).

According to Moon (2002), a computer is perceived as expert and more competent if its messaging style aligns with its personality. Aggarwal and Mcgill (2007) also discovered that people possessing a sound knowledge of human actions, anatomy, and experiences could easily understand intelligent products that look like them, thanks to the accessibility of these schemes. The perceptual accessibility of a product should result in a greater intention to utilize it for enjoyment and convenience purposes. Similarly, (Han, 2021) indicated that Consumers' perception of chatbot anthropomorphism influences chatbot purchase intention. The following hypothesis is subsequently proposed:

H8. Consumers' perception of voice assistant anthropomorphism will positively influence their continued usage intention of this service.

2.3.9. Perceived intelligence and continued usage intention

The perceived intelligence of a service robot is based on how much it intellectually mimics human behavior (Qiu et al., 2020). Robots are enabled with intelligence technologies and can mimic human senses, detect and recognize their voices and body movements, perceive and interpret their facial expressions and feedback, and understand their activities (Tung and Au, 2018). The perceived intelligence was assessed in the human-robot interaction literature by questioning users and requesting them to rate the robot's competence, knowledge, responsibility, intelligence, and sensitivity (Moussawi and Benbunan-Fich, 2021).

Competence is crucial in purchases made with the use of advanced technology. Cross-cultural communication competence has been observed to positively impact purchase intention (Ihtiyar and Ahmad, 2014). Bassellier et al. (2001) affirmed that systems intelligence was primarily responsible for technical competence.

McLean et al. (2021) revealed that the perceived intelligence of artificial voice assistants would positively influence the brand loyalty of consumers. Tussyadiah and Park (2018) observed that the willingness of consumers to indulge in the use of hotel service robots is statistically influenced by their perception of robot intelligence. Against this background, Balakrishnan and Dwivedi (2021) implied that through the use of digital assistants, users' purchasing intent would be positively influenced by perceived intelligence. Respectively, Tussyadiah and Park (2018) discovered that the adoption intention of individuals is positively influenced by their perceived intellect. Based on this evidence, the following hypothesis is proposed:

H9. Perceived intelligence positively influences the continued usage intention of voice assistants.

2.3.10. Attractiveness, trustworthiness, and expertise with brand's loyalty

Brand attractiveness is defined as the positive assessment of the brand's core, distinctive, and persistent connotations and features (Ahearne et al., 2005).

[1] Quality and price are noted as functional values denoted by quality and monetary values. Refer to Sweeney and Soutar (2001) and Putrianti and Semuel (2018) for more discussion on the four dimensions.

Individuals tend to find a brand appealing if it affords them the opportunity to satisfy one of three essential needs: self-continuity, self- distinctiveness, or self-enhancement (Noh and Johnson, 2019). According to Tsai and Pei (2011), when a brand's attractiveness is expressed in terms of its financial value, performance outcomes and functional distinctiveness dwindle, with the original brand loyalty dwindling or even evaporating. Elbedweihy et al. (2016) revealed that the perception of a brand as being attractive by customers, prompted by the fulfillment of self-definitional needs, contributes to both brand loyalty and serves as a disposition to dismiss any unpleasant information acquired about the brand. Correspondingly, Islam et al. (2014) discovered a substantially positive association between attractiveness and brand loyalty.

Trustworthiness is important in developing buyer-seller interactions and fostering exchange relationships (Kharouf et al., 2014). As defined by McKnight et al. (2002), trustworthiness is the perceived likelihood that a particular fiduciary will retain the customer's trust. According to Sekhon et al. (2014), trustworthiness is regarded as a foundation for judgment development, as it possesses a strong positive influence on customer loyalty (Kharouf et al., 2014). Brand loyalty can be built by establishing bonds and interactions with customers (Gustafsson et al., 2005). Owing to the generation of highly valued connections, brand trustworthiness affects customers' brand loyalty (Alam et al., 2012). Abbasi et al. (2011) further discovered that trustworthiness impacts the ability of a product to satisfy a consumer's expectations and thus, serves as an important predictor of customer loyalty. Likewise, Singla and Gupta (2019) discovered a positive and significant link between brand loyalty and trustworthiness. The creators of digital voice assistants must promote trustworthiness, responsibly address privacy issues, and create a trustworthy climate for their customers to interact with and remain loyal to their companies.

Another facet attached to trustworthiness is expertise. Consumers' perceptions of the endorser's experience and the corresponding knowledge of the endorsed product are expressed by expertise (Ohanian, 1990). Competence, know-how, professional ability, and self- assuredness have all been linked to expertise (Han and Ki, 2010). Additionally, different groups of customers tend to have varying expertise levels, resulting in variations in customers' loyalty to the service brand. Users may sometimes possess a greater understanding or skills relating to the service offering than others and may not exhibit an equal level of loyalty to the service provider (Jamal and Anastasiadou, 2009). Consumer expertise, according to past studies, may have a favorable impact on customer loyalty (Bell et al., 2017), leading to the proposition of the following hypothesis:

H10. Attractiveness has a positive influence on brand loyalty.

H11. Trustworthiness positively and significantly influences brand loyalty.

H12. Expertise positively and significantly influences brand loyalty.

2.3.11. Continued usage intention and loyalty

Drawing from the work of Ajzen and Fishbein (1975) on intention to use, the authors opine that continued usage intention can be an essential phase in the behavior implementation procedure, “which in turn impacts their behavioral intention towards continued usage of voice assistants” (Jain et al., 2022). Previous studies have agreed on the non- existence of a significant relationship between behavioral intention and loyalty (Anderson et al., 2014). Moreover, customer loyalty is considered an essential factor in the success of a technology (Chang and Chen, 2009). Therefore, the following hypothesis is proposed:

H13. The relationship between continued usage intention and brand loyalty is significant.

2.3.12. The moderating impact of brand credibility

Researchers of consumer-based brand equity using signaling theory, Erdem and Swait (1998) were also the introducers of the concept of brand credibility. Brand credibility is the belief in a product's positioning information that is stored in a brand based on customers' assessment of the brand's ability and willingness to consistently deliver what is promised (Baek and King, 2011). Brand credibility is commonly understood to comprise two major components: trustworthiness and
expertise (Erdem and Swait, 1998). Expertise refers to the ability of a company to fulfill its promises, while trustworthiness refers to the willingness of a company to keep its promises. As a brand's trustworthiness and competence are built on the cumulative effect of all prior marketing activities and strategies, brand credibility is not expected to echo the steadiness of marketing mix techniques across brand investments such as advertising (Baek et al., 2010).

Brand credibility predates the assessments and intents of customers relating to a brand. It promotes customer brand assessments, consideration, and decisions (Erdem and Swait, 1998). Brand credibility enhances the perceived quality and lowers perceived risk and information costs, which in turn improves the desired utility of customers (Mandler et al., 2021). Therefore, customers' impression of a brand's qualities increases with brand credibility (Pratihari and Uzma, 2018). Smart marketing communication and advertising can leverage this to enhance purchasing intention (Jahdi and Acikdilli, 2009). Voice-activated and conversational AI such as Alexa and Siri has improved the efficiency of healthcare for those unable to leave their homes when ill. Given these characteristics of brand credibility, VAs from trustable brands is expected to increase the users' task effectiveness and overall efficiency, leading to a higher perceived value by satisfying the needs and wants of users. Alternatively, VAs from lesser-known brands might have more difficulty conveying their utility features to their users' perceived value in enhancing their experience or satisfaction, for example, due to less effective marketing or branding activities. Hence, the following hypothesis is proposed:

H14a. Brand credibility moderates the relationship between the utility features and overall perceived value.

According to previous research, consumption motives may be classified as either product-oriented (utilitarian) or experience-oriented (hedonic) (Hirschman and Holbrook, 1982). A more recent study similarly emphasized the significance of the hedonic qualities of technology (Jamshidi et al., 2018). For example, Childers et al. (2001) discovered that diverse technological aspects, such as hedonic and utilitarian, influence the relative relevance of ease of use, usefulness, and enjoyment. Asides from enjoyment, the pleasure of using new technology may influence a variety of characteristics of its future use (Jain et al., 2022). Mattila and Wirtz (2000) suggested that the dimensions of enjoyment and pleasure interact in defining customers' assessments of the technology, followed by the formation of trust in the technology (Gefen et al., 2003). The literature widely acknowledges that the context in which users are interacting with a new product significantly affects their emotional satisfaction manifested in the hedonic features of the product. Indeed, hedonic-motivated users tend to focus more on the preexisting product interaction experience and process. It means customers having a more satisfying experience with a specific brand and considering it more credible in terms of attractiveness, trustworthiness, and expertise are more likely to draw on their perceptual hedonic (emotional) satisfaction to understand their experience with the product as more valuable and satisfactory. Hence, the following hypothesis is proposed: **H14b**. Brand credibility moderates the relationship between the hedonic features and overall perceived value.

Several studies have demonstrated that the manner of assessment and reaction to artificial agents is heavily influenced by their social presence (Pitardi and Marriott, 2021). The machine-generated voice may express social presence by imitating specific human characteristics (Kim et al., 2013). Lee and Nass (2005) discovered that consumers felt a more social presence when they heard a machine-generated voice that was comparable to their own voice pitch or that of a pleasant personality (extroverted). Also, according to Amazon customer reviews, a voice assistant is more pleasant when customers can engage in a social conversation with them (Shao and Kwon, 2021). Users may be capable of distinguishing different brands and perceive their voice assistant's voice as its own character, depending on the quality of engagement. Moreover, a human form is more likable than a robotic presence. Therefore, brand credibility is important in improving consumer social comfort and perceived value (Jain et al., 2022). In particular, VAs from credible brands is assumed to be perceived as more technologically advanced, capable, trustful, honest, and believable. Hence, we propose that VAs from highly regarded brands have the technological competencies to convey a better sense of human contact, personal touch, sociability, and human warmth. Based on the discussion above, we hypothesize the following:

H14c. Brand credibility moderates the relationship between social presence and overall perceived value.

Concerns regarding the possible exposure and lack of control over personal information are referred to as perceived privacy risks (Vimalkumar et al., 2021). Consumers' sense of privacy risks, especially in the secondary data uses, tends to diminish their trust in websites (Martin, 2018). As large technology companies have developed voice-based assistants, users may have privacy concerns that may discourage their usage (Rauschnabel et al., 2018).

Perceived privacy risk tends to reduce consumers' trust in voice- activated assistants (Dinev and Hart, 2006) and may also affect their privacy concerns. By and large, users often lower their risk perceptions by opting for only credible brands (Baek, 2007). Thus, brands have long been deemed an important component in building customer trust (Chaudhuri and Holbrook, 2001). As noted by Myerscough et al. (2008), the perceived privacy risk is significantly higher for weaker brands as opposed to stronger ones. Accordingly, we assume that for VAs offered by reputable brands, users consider them more valuable and satisfactory since they are perceived to be less prone to privacy risks such as confidentiality loss or information misuse. Conversely, we assume users to be more concerned with VAs' privacy issues while interacting with lesser- known brands and experiencing less value delivered to them due to constantly experiencing the threat of information and privacy loss. Therefore, the following hypothesis is proposed:

H14d. The relationship between perceived privacy risk and overall perceived value is weaker when the brand credibility is high.

Perceived irritation has been observed to negatively influence the mood, satisfaction, ease of use, word of mouth, return intention, and purchase behavior of online shoppers (Jere and Davis, 2011; Thota, 2012). Some users become annoyed when their voice assistants do not comprehend or respond to their voice commands (Salai et al., 2021).

Brand credibility translates to a risk-minimization method for consumers, owing to their belief in brand specifications and the possession of a compelling psychological motivation about the product's value (Othman et al., 2017). A study conducted by (Cuong, 2020) demonstrated that brand credibility had quite a significantly positive impact on consumer satisfaction, perceived value, and purchase intention. Consistently, we believe that users tend to alleviate their negative feelings of irritation when interacting with pleasantly branded VAs and dealing with the potential sense of confusion, dumbness, disturbance, or mistrust resulting from using VAs, thus, perceiving higher satisfaction or valuable experience when utilizing them. By the same logic, we expect users to overmagnify their sense of irritation when interacting with VAs of lesser-known and reputable brands, perceiving less satisfying and memorable experience. Therefore, the following hypothesis is proposed: **H14e**. The association of perceived privacy risk with the overall perceived value tends to be weaker when brand credibility is high.

2.3.13. The moderating impact of age

Age-related research has concentrated on the differences in cognitive assessments of products or services among old and young customers. Commonly, for any purchase decisions, older customers tend to depend heavily on heuristic processing while the younger ones seek out multiple information channels (Yoon, 1997). In particular, older consumers prefer to base purchases on prior usage, while the younger ones are more prone to making purchases on an information basis (Homburg and Giering, 2001). As a result, it is logical to highlight that consumer in the older age bracket is more loyal than younger ones, given the same product or service performance level. In contrast, Morris and Venkatesh (2000) discovered that age differences might negatively moderate attitudes toward technology adoption. Likewise, Chaouali and Souiden (2019) established a link between functional or psychological hurdles and aversion to online banking and discovered that aversion varied greatly by age group. However, the existing literature does not examine age-based demographic factors in justifying the differences in technology adoption. Therefore, the following hypotheses are proposed:

H15a–H15e. A significant difference will exist in the path estimates proposed from hypotheses 1 to 5 for variances within age groups.

2.3.14. The moderating impact of gender

An understanding of gender disparities in individual adoption and technology usage is critical to organizational psychologists attempting to navigate the organizational transformation process (Venkatesh, 2000). The views of women on the usage of technology may vary and evolve over time as technology becomes more prevalent than ever and becomes a vital element of life, particularly for the younger generation (Buccheri et al., 2011). Li et al. (2008) offered a foundation for the expectation of gender differences in the importance of instruments in decision-making processes. They suggested that women are less likely to adopt new technologies than men. As revealed in the study by Cai et al. (2017), males continue to possess more positive sentiments. On the contrary, Mittal and Kamakura (2001) discovered that women were much more open-minded and that, given a similar level of satisfaction, their repurchase intention was greater than that of men. Therefore, the following hypothesis is proposed:

H16a–H16e. A significant difference is anticipated in the path estimates recommended from hypotheses 1 to 5 within gender groups.

3. Research methodology

3.1. Data collection and samples

The purposive sampling approach was utilized in this research, which is one of the most common kinds of non-probability sampling in which units are chosen with a specific aim in mind. According to Daniel (2011), “in purposive sampling the researcher purposely selects the elements because they satisfy specific inclusion and exclusion criteria for participation in the study”. Kumar (2018) concluded that adopting a purposive sampling approach is very appropriate when researchers need to explain an event or gain new information about a phenomenon about which little was previously known. Notably, purposive sampling is susceptible to bias and errors, and the research team strictly applied the following widely accepted rules or procedures to warrant the reliability and validity of the sampling efforts:

- Carefully studying the population to understand its demographic mix and choosing eligible participants in line with the research objectives;
- Designing and integrating an online self-assessment tool within the survey to ensure the eligibility of participants (e.g., in terms of being actual users of VAs);
- Simplicity, understandability, and accessibility of the online survey instrument;
- Following up on the nonresponders and collecting their opinions.

The present study was conducted in China, and the sampling frame consisted of Chinese adults who were the existing users of AliGenie, Alibaba's intelligent personal assistant, via the Tmall Genie smart device or application. G*Power software, the most powerful analytic package for a range of statistical tests in the behavioral and social sciences, was used to compute the sample size for this research (Cohen, 1992). According to G*power 3.1.9.2 statistics, the required minimum sample size should be >127 respondents with $f^2 = 0.15$ (effect size), $\alpha = 0.05$ (error type one), $\beta = 0.20$ (error type two) (Cohen, 1992). The total sample obtained for the main study (N = 426) is large enough to test the parameters of this model, according to the aforementioned criteria and the statistical analysis strategy used for this research.

To test the hypotheses, an online survey (questionnaire) was created. The components of the questionnaire were developed using existing literature and then adjusted to fit the research parameters. Customers of Alibaba, the world's largest online commerce firm, formed the population of the study. These individuals were surveyed via an online questionnaire between mid-September and the end of November 2021. After we deleted all the partial or ungiven responses, a final sample was 426. The number of valid responses received was 426, which was deemed sufficient to investigate the parameters of the suggested model. Table 2 provides information on the demographic characteristics of the participants in this research.

3.2. Construct measures

The constructs involved in this study are utility features, hedonic features, social presence, irritation, perceived privacy risk, perceived value, continued usage intention, brand loyalty, perceived anthropomorphism, perceived intelligence, attractiveness, trustworthiness, and expertise. The primary construct measurements were derived from previous research. Items were changed to meet the context of the voice assistant. The utility features' items were derived from Davis (1989) and Venkatesh (2000). The hedonic feature measurements were derived from Al-Natour et al. (2011). Four social presence-related items were selected from Al-Natour et al. (2011). Items pertaining to perceived privacy risk were gathered from Yang et al. (2017). Irritation measurements were adapted from Liu et al. (2012), Boateng et al. (2016), and Dar et al. (2014). Three overall perceived value components were adapted from Cronin et al. (2000). The measures for continued usage intention were derived from Bhattacherjee (2001). The three items of perceived anthropomorphism were adopted from Balakrishnan and Dwivedi (2021). Items for perceived intelligence, brand loyalty, attractiveness, trustworthiness, and expertise were drawn from the study of Balakrishnan and Dwivedi (2021). For all questions, a five-point Likert scale ranging from “(1) strongly disagree” to “(5) strongly agree” was utilized. Appendix A outlines the independent variable measurement items.

4. Analysis and results

PLS-SEM analysis in this study consists of assessing measurement models, the structural model, and the assessment of moderating effects.

Table 2
Demographics of respondents.

Demographics	Frequency	Percentage
Gender		
Male	222	52.1 %
Female	204	47.9 %
Age range		
<20	36	8.5 %
20–25	71	16.7 %
25–30	76	17.8 %
30–35	52	12.2 %
>35	191	44.8 %
Profession		
Student	54	12.7 %
Working professional	273	64.1 %
Business professional	82	19.2 %
Housewife	17	4.0 %

Each of these analyses is explained in the following sections.

4.1. Assessment of measurement models

Following the widely accepted procedure within the PLS-SEM literature (e.g., Hair et al., 2017), the assessment of reflective measurement models in the present study involves the evaluation of internal consistency, convergent validity, and discriminant validity.

Cronbach's alpha is the traditional and widely accepted criterion for assessing internal consistency reliability. Cronbach's alpha varies between 0 and 1, and values of 0.7 or higher indicate adequate internal consistency for measurement items (Hair et al., 2019). Cronbach's alpha is a conservative measure of internal consistency, given that it is sensitive to the number of items. Thus, Cronbach's alpha is commonly complemented by the composite reliability criterion. As a general rule of thumb, a composite reliability value of >0.6 in exploratory research or >0.7 in confirmatory research indicates satisfactory internal consistency (Hair et al., 2017). As shown in Table 3, all Cronbach's alpha and composite reliability values for constructs are equal to or exceed the 0.7 threshold. Thus, the

internal consistency reliability of the measurement models is adequate. Since none of the consistency reliability values exceeded the 0.95 cut-off value, the issue of semantically redundant items is of no concern in this study.

Convergent validity evaluates to what extent an indicator (measure) correlates positively with other indicators of the same construct. In PLS- SEM analysis, the indicator ‘outer loading’ and Average Variance Extracted (AVE) are the two widely accepted measures of convergent validity. In general, a standardized outer loading of 0.708 or higher and an AVE value of 0.5 or higher can collectively indicate an adequate convergent validity (Hair et al., 2017). Table 3 indicates that all outer loading and AVE values adhere to the rule above of thumb. Thus, there is sufficient evidence of convergent validity.

Discriminant validity draws on empirical standards to explain to what extent a given construct is accurately distinct from other constructs of the general measurement model (Hair et al., 2019). The Fornell- Larcker criterion (Fornell and Larcker, 1981) was used for assessing the discriminant validity. The Fornell-Larcker criterion compares the square root of the AVE values against the correlations of constructs (latent variables). For the Fornell-Larcker criterion to validate the discriminant validity, the square root of AVE for a given construct must be greater than all its correlation values (Hair et al., 2017). Table 4 explains that all constructs satisfy the Fornell-Larcker criterion in the present study, meaning each of the constructs shares more variance with its respective items (indicators) than with any other latent variables. It is important to note that cross-loadings the Fornell Larcker criteria fall short in applicability under certain circumstances. Henseler et a. (2015) recommend measuring the heterotrait-monotrait ratio (HTMT) of the correlations to address this issue. Overall, the HTMT values of 0.90 or higher suggest a lack of discriminant validity (Hair et al, 2017). Table 5 shows the HTMT matrix within which none of the HTMT exceed this threshold. Thus, the results in Tables 4 and 5 collectively point to a satisfactory discriminant validity.

4.2. Assessment of structural model

The structural model assessment in this study follows the standard procedure recommended by X, which includes examining the structural model's collinearity issues, significance and relevance of relationships, coefficient of determination (R^2), f^2 effect size, and predictive relevance (Q^2).

Fig. 2 and Table 6 list the results of the assessment of the structural model. According to Hair et al. (2017), a VIF value of 5 or higher indicates a critical level of collinearity. Table 6 indicates that none of the inner VIF values for hypothesized relationships exceeds the cut-off value of 5, meaning collinearity is of no concern within structural analysis results. Table 6 further shows the structural model path coefficients and their respective statistical significance levels.

Table 3

Properties of reflective measurement models.

Item	Outer loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Attractiveness (ATR)		*0.81*	*0.89*	*0.73*
ATR1	0.88			
ATR2	0.86			
ATR3	0.82			
Brand loyalty (BRL)		*0.80*	*0.87*	*0.62*
BRL 1	0.82			
BRL 2	0.84			
BRL 3	0.73			
BRL 4	0.77			
Expertise (XPR)		*0.87*	*0.91*	*0.71*
XPR 1	0.89			
XPR 2	0.81			
XPR 3	0.80			
XPR 4	0.88			
Hedonic features (HDF)		*0.70*	*0.83*	*0.62*
HDF1	0.78			
HDF2	0.74			
HDF3	0.84			
Irritation (IRR)		*0.79*	*0.86*	*0.61*
IRR1	0.83			
IRR2	0.72			
IRR3	0.77			
IRR4	0.80			
Overall perceived value (OPV)		*0.71*	*0.84*	*0.63*
OPV1	0.80			
OPV2	0.83			
OPV3	0.75			
Perceived anthropomorphism (PAP)		*0.70*	*0.83*	*0.62*
PAP1	0.73			
PAP2	0.82			
PAP3	0.82			
Perceived intelligence (PCI)		*0.77*	*0.85*	*0.59*
PCI1	0.80			
PCI2	0.75			

PCI3	0.72			
PCI4	0.80			
Perceived privacy risk (PPR)		*0.81*	*0.89*	*0.73*
PPR1	0.87			
PPR2	0.83			
PPR3	0.86			
Social presence (SCP)		*0.74*	*0.84*	*0.57*
SCP1	0.75			
SCP2	0.71			
SCP3	0.79			
SCP4	0.76			
Trustworthiness (TRW)		*0.84*	*0.89*	*0.68*
TRW1	0.89			
TRW2	0.83			
TRW3	0.82			
TRW4	0.74			
Utility features (UTF)		*0.76*	*0.86*	*0.67*
UTF1	0.83			
UTF2	0.80			
UTF3	0.83			
Voice Assistant Continued Usage Intention (VCU)		*0.85*	*0.91*	*0.77*
VCU1	0.89			
VCU2	0.87			
VCU3	0.88			

The results explain that utility features ($\beta = 0.18$, $p < 0.01$), hedonic features ($\beta = 0.26$, $p < 0.01$), and social presence ($\beta = 0.22$, $p < 0.01$) have a significant positive effect on overall perceived value. Perceived privacy risk ($\beta = -0.31$, $p < 0.01$) and irritation ($\beta = -0.22$, $p < 0.01$) have a significant negative effect on overall perceived value. Thus, H1, H2, H3, H4, H5 are respectively accepted. These independent variables collectively account for 56 % of the variance in overall perceived value ($R^2 = 0.56$). Perceived privacy risk is the most substantive determinant of overall perceived value, given that it has the largest effect size ($f^2 = 0.18$). Results also signify the acceptance of H6 and H7, given that overall perceived value significantly and positively determines voice assistant continued usage intention ($\beta = 0.28$, $p < 0.01$) and brand loyalty ($\beta = 0.20$, $p < 0.01$). Perceived anthropomorphism ($\beta = 0.22$, $p < 0.01$) and perceived intelligence ($\beta = 0.30$, $p < 0.01$) have a significant positive effect on voice assistant continued usage intention, which means the acceptance of H8 and H9. Overall perceived value, perceived anthropomorphism, and perceived intelligence collectively explain 33 % of the variance in voice assistant continued usage intention ($R^2 = 0.33$). Table 6 explains that perceived intelligent is the most substantive determinant among these three variables, with an f^2 effect size of 0.12.

Results further reveal that trustworthiness ($\beta = 0.20$, $p < 0.01$), expertise ($\beta = 0.27$, $p < 0.01$), and voice assistant continued usage intention ($\beta = 0.22$, $p < 0.01$) have a significant positive effect on brand loyalty, which translates to the acceptance of H11, H12, and H13. However, the effect of attractiveness on brand loyalty was statistically insignificant ($\beta = 0.09$, $p > 0.05$), which means the rejection of H10. The four direct determinants of brand loyalty collectively accounted for 42 % of variance explained in this variable ($R^2 = 0.42$). Expertise with an f^2 effect size of 0.08 is considered the most substantive determinant of brand loyalty.

Finally, the study assessed the predictive relevance of endogenous reflective latent variables of the structural model to ensure the model's out-of-sample predictive power. To this end, the study conducted the blindfolding analysis with the Omission Distance of 7 to calculate the Stone-Geisser's predictive relevance (Q^2) values (Geisser, 1974; Stone, 1974). The general guideline explains that the structural model offers adequate predictive relevance for a given endogenous construct when its respective Q^2 value is larger than 0. The Q^2 values for the three endogenous constructs of the present study, namely brand Loyalty, overall perceived value, and voice assistant continued usage intention, are 0.25, 0.35, and 0.24. Therefore, there is sufficient evidence of predictive relevance in the structural model.

4.3. Moderation analysis

The study conducted the two-stage approach proposed by (Chin et al., 2003) for assessing the hypotheses related to the moderating effects of brand credibility and age. The study selected the two-stage approach against alternatives such as the product indicator approach or orthogonalizing approach because the two-stage approach is more appropriate when the moderators are measured formatively (e.g., brand credibility) or as a single item (Hair et al., 2017). This study has followed the existing guides (e.g., Hair et al., 2017) and constructed brand credibility as a second-order Hierarchical Component Model (HCM) measured formatively by three latent variables of attractiveness, trustworthiness, and expertise, measured reflectively. To prepare the moderator for the two-stage approach, the two-stage HCM analysis was first conducted (Henseler and Chin, 2010). In doing so, the first step involved using the repeated indicator approach to attain the latent variable scores for the three lower-order constructs of attractiveness, trustworthiness, and expertise, measured reflectively. The second step involved using the latent variable scores of the three lower-order constructs to represent as manifest variables in the brand credibility higher- order component measurement model. The two-stage HCM requires ensuring the validity and reliability of reflective and formative measurement models across the two stages of analysis. The reflective measurement model analysis results for the lower-order constructs of attractiveness, trustworthiness, and expertise revealed that all Cronbach's alpha and composite reliability values for constructs are equal to or exceed the 0.7 threshold, indicating adequate internal consistency reliability.

Table 4

The assessment of Fornell-Larcker criterion.

Construct	ATR	BRL	XPR	HDF	IRR	OPV	PAP	PCI	PPR	SCP	TRW	UTF	VCU
ATR[a]	*0.85*[b]												
BRL	0.36	*0.79*											
XPR	0.43	0.50	*0.84*										
HDF	0.13	0.24	0.11	*0.79*									
IRR	0.01	− 0.08	− 0.01	0.01	*0.78*								
OPV	0.21	0.40	0.20	0.51	− 0.31	*0.79*							
PAP	0.06	0.19	0.10	0.07	− 0.12	0.24	*0.79*						
PCI	0.18	0.28	0.11	0.13	− 0.08	0.31	0.24	*0.77*					
PPR	− 0.10	− 0.28	− 0.12	− 0.33	0.19	− 0.55	− 0.08	− 0.17	*0.85*				
SCP	0.11	0.23	0.11	0.35	− 0.09	0.49	0.12	0.17	− 0.24	*0.75*			
TRW	0.42	0.45	0.50	0.13	− 0.05	0.20	0.06	0.14	− 0.11	0.11	*0.82*		
UTF	0.07	0.30	0.13	0.41	− 0.08	0.49	0.09	0.18	− 0.33	0.43	0.11	*0.82*	
VCU	0.16	0.42	0.24	0.24	− 0.20	0.43	0.36	0.44	− 0.27	0.29	0.17	0.28	*0.88*

[a] Attractiveness, ATR; Brand loyalty, BRL; Expertise, XPR; Hedonic Features, HDF; Irritation, IRR; Overall Perceived Value, OPV; Perceived Anthropomorphism, PAP; Perceived Intelligence, PCI; Perceived Privacy Risk, PPR; Social Presence, SCP; Trustworthiness, TRW; Utility Features, UTF; Voice Assistant Continued Usage Intention, VCU.

[b] The *italic* items on the diagonal represent the square roots of the AVE.

Table 5

The HTMT matrix.

Construct	ATR	BRL	XPR	HDF	IRR	OPV	PAP	PCI	PPR	SCP	TRW	UTF	VCU
ATR[a]													
BRL	0.45												
XPR	0.50	0.59											
HDF	0.17	0.33	0.14										
IRR	0.06	0.15	0.06	0.10									
OPV	0.27	0.53	0.25	0.73	0.40								
PAP	0.10	0.25	0.12	0.13	0.16	0.34							
PCI	0.22	0.36	0.13	0.18	0.10	0.41	0.33						
PPR	0.12	0.34	0.14	0.44	0.22	0.72	0.11	0.21					
SCP	0.14	0.30	0.14	0.49	0.11	0.67	0.17	0.22	0.31				
TRW	0.51	0.54	0.58	0.16	0.10	0.25	0.08	0.17	0.13	0.14			
UTF	0.09	0.38	0.17	0.56	0.11	0.68	0.13	0.24	0.41	0.57	0.14		
VCU	0.19	0.50	0.28	0.31	0.24	0.54	0.47	0.54	0.32	0.36	0.20	0.35	

[a] Note: Attractiveness, ATR; Brand loyalty, BRL; Expertise, XPR; Hedonic Features, HDF; Irritation, IRR; Overall Perceived Value, OPV; Perceived Anthropomorphism, PAP; Perceived Intelligence, PCI; Perceived Privacy Risk, PPR; Social Presence, SCP; Trustworthiness, TRW; Utility Features, UTF; Voice Assistant Continued Usage Intention, VCU.

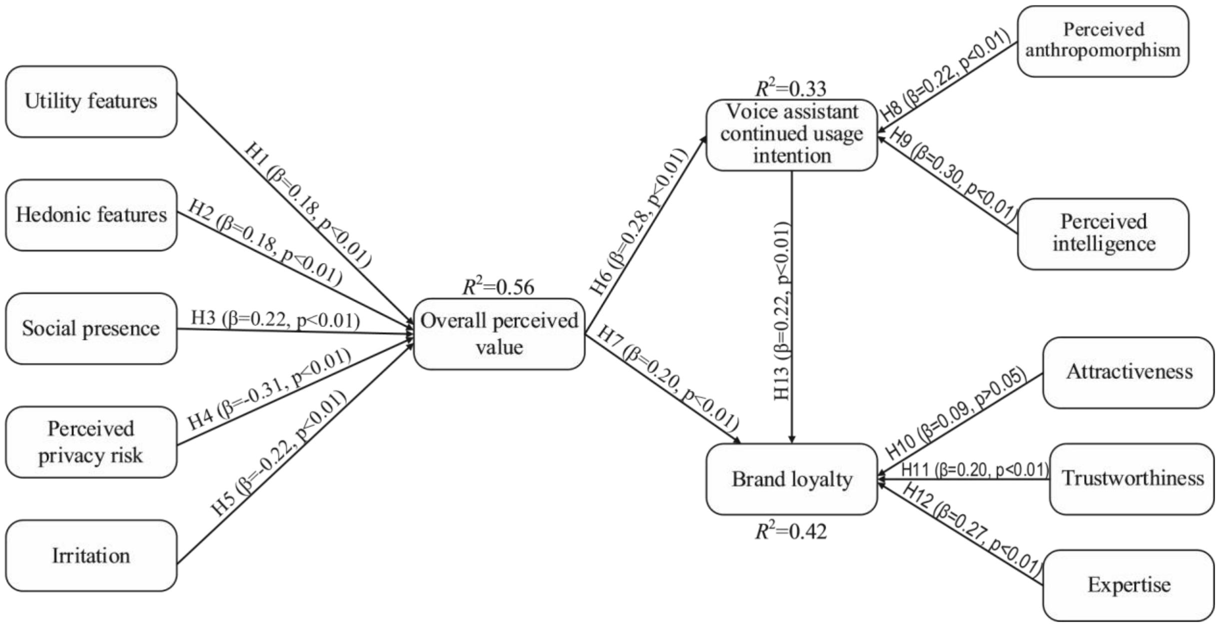


Fig. 2. Results of structural path analysis.

Table 6
Structural path analysis results.

Path	Hypothesis	Path coefficient	p-value	*t* value	Effect size (f^2)	VIF
Utility features → Overall perceived value	H1	0.18	0.00	3.63	0.05	1.40
Hedonic features → Overall perceived value	H2	0.26	0.00	6.57	0.12	1.32
Social presence → Overall perceived value	H3	0.22	0.00	5.34	0.09	1.30
Perceived privacy risk → Overall perceived value	H4	− 0.31	0.00	7.59	0.18	1.23
Irritation → Overall perceived value	H5	− 0.22	0.00	6.89	0.11	1.05
Overall perceived value → Voice assistant continued usage intention	H6	0.28	0.00	5.62	0.10	1.14
Overall perceived value → Brand loyalty	H7	0.20	0.00	4.23	0.05	1.26
Perceived anthropomorphism → Voice assistant continued usage intention	H8	0.22	0.00	5.13	0.07	1.10
Perceived intelligence → Voice assistant continued usage intention	H9	0.30	0.00	6.51	0.12	1.14
Attractiveness → Brand loyalty	H10	0.09	0.053	1.94	0.01	1.33
Trustworthiness → Brand loyalty	H11	0.20	0.00	4.24	0.05	1.44
Expertise → Brand loyalty	H12	0.27	0.00	5.75	0.08	1.48
Voice assistant continued usage intention → Brand loyalty	H13	0.22	0.00	4.97	0.07	1.26

Moreover, all outer loadings were well above 0.7, and AVE values were over 0.5 for these three reflective measurement modes, providing sufficient evidence of convergent validity. The cross-loadings and the Fornell-Larcker criteria were also assessing, indicating adequate discriminant validity. As the second step in the -stage HCM approach, the formative measurement model of brand credibility (constructed by the latent scores of attractiveness, trustworthiness, and expertise) was assessed. None of the formative indicators showed a VIF value of higher than 5, indicating an acceptable level of collinearity. The bootstrapping results with 5000 subsamples also indicated that the three formative indicators of attractiveness, trustworthiness, and expertise have statistically significant outer weights at the 5 % significance level ($\alpha = 0.05$; two-tailed test). Overall, the two-stage HCM ensured the necessary reliability and validity of the brand credibility construct to serve as the moderator in the two-stage approach.

Fig. A1 shows the results of the two-stage approach for assessing hypotheses related to the moderating effect of brand credibility. This figure also depicts the slope plots related to each moderation hypothesis. The results of the two-stage approach analysis with 5000 bootstrap subsamples reveal that brand credibility does not have a significant moderating effect on the relationships between brand credibility and overall perceived value ($\beta_{IT} = -0.01$, $p > 0.05$), hedonic features, and overall perceived value ($\beta_{IT} = -0.03$, $p > 0.05$), social presence and overall perceived value ($\beta_{IT} = -0.03$, $p > 0.05$), and irritation and overall perceived value ($\beta_{IT} = 0.02$, $p > 0.05$). Therefore, H14a, H14b, H14c, and H14e are, respectively, rejected. In contrast, results show that brand credibility has a significant moderating effect on the relationship between perceived privacy risk and overall perceived value ($\beta_{IT} = 0.09$, $p < 0.01$), indicating the acceptance of H14d. This finding shows that the relationship between perceived privacy risk and overall perceived value would decrease to $-0.31 + (0.09) = -0.22$ if the mean value of brand credibility increases by one standard deviation unit.

The results of the two-stage approach for assessing hypotheses related to the moderating effect of age are presented in Fig. A2. Results reveal that age significantly moderates the relationship between utility features and overall perceived value ($\beta_{IT} = -0.14$, $p < 0.01$), which means H16a is accepted. It means the relationship between utility features and overall perceived value would decrease to $0.18 + (-0.14) = 0.04$ if the mean value of age increases by one standard deviation unit. Yet, age does not have a significant moderating effect on the relationship between hedonic features and overall perceived value ($\beta_{IT} = -0.04$, $p > 0.05$), indicating the rejection of H16b. Results further show that social presence exerts a significant moderating effect on the relationship between social presence and overall perceived value ($\beta_{IT} = -0.11$, $p < 0.01$), leading to the acceptance of H16c. This finding means the relationship between social presence and overall perceived value would decrease to $0.22 + (-0.11) = 0.11$ if the mean value of age increases by one standard deviation unit. Finally, the results show that age does not significantly moderate the relationships between perceived privacy risk and overall perceived value ($\beta_{IT} = -0.01$, $p > 0.05$) and irritation and overall perceived value ($\beta_{IT} = -0.05$, $p > 0.05$). Therefore, H16d and H16e are, respectively, rejected.

The study uses multi-group analysis to assess the hypotheses related to the moderating role of gender. Hair et al. (2017) propose that the PLS- MGA analysis is the more appropriate non-parametric approach for multi-group analysis when two distinct groups have unequal sample sizes. The study drew on the built-in

MGA analysis of the SmartPLS software to test for the statistical difference in gender-specific results. This MGA analysis builds on the Henseler and Chin (2010) PLS-MGA method, which compares the bootstrap estimates of the two groups (including standard errors) against each other. Thus, bootstrapping with 5000 subsamples was used for conducting the PLS-MGA analysis on male and female groups. Table 7 explains the results of the PLS-MGA analysis, in which the p-values account for the two-sided test. Results show that the influence of utility features on overall perceived value does not statistically differ among male and female groups of respondents ($|\Delta\beta| = 0.10$, $p > 0.05$), which indicates the rejection of H15a. Nonetheless, gender significantly moderates the relationships between hedonic features and overall perceived value ($|\Delta\beta| = 0.25$, $p < 0.01$) and social presence and overall perceived value ($|\Delta\beta| = 0.18$, $p < 0.05$). Accordingly, H15b and H15c are accepted. This finding means that the influences of hedonic features and social presence on overall perceived value have been positively stronger among females. Results also reveal that gender moderates the influence of perceived privacy risk ($|\Delta\beta| = 0.23$, $p < 0.05$) on overall perceived value, leading to the acceptance of H15d. This finding explains that the influence of perceived privacy risk on overall perceived value has been negatively stronger among males. Finally, Table 7 reveals that the influence of irritation on overall perceived value is not statistically different among the male and female groups ($|\Delta\beta| = 0.07$, $p > 0.05$), leading to the rejection of H15e.

Table 7
Multi-group analysis results for the moderating role of gender.

Relationship	Group 1: male		Group 1: female		Male group vs. female group		
	P^m	SD^m	P^f	SD^m	$\|P^m - P^f\|$	*t* value	p-value
Utility features → Overall perceived value	0.13	0.07	0.23	0.05	0.10	1.18	0.24
Hedonic features → Overall perceived value	0.15	0.05	0.40	0.06	0.25	3.30	0.00
Social presence → Overall perceived value	0.30	0.06	0.12	0.06	0.18	2.21	0.03
Perceived privacy risk → Overall perceived value	− 0.39	0.05	− 0.16	0.06	0.23	2.80	0.01
Irritation → Overall perceived value	− 0.24	0.04	− 0.17	0.08	0.07	0.81	0.42

5. Discussion

This study deployed the U&GT, signaling, and prospect theories with several variables to examine the perception of individuals and their behavioral intention toward the use of voice assistants. The empirical results of the current study revealed that the path coefficient analyses between utility and hedonic features alongside the perceived value of voice assistants were significant, corroborating hypotheses H1 and H2. The results align with the discoveries from previous studies conducted by Jain et al. (2022) with a similar nature of voice assistants. By comparing utility and hedonic features, the study discovered that participants placed higher value on hedonic features than utility features, despite the significance of the bootstrapping results for both features. Our results are thus consistent with the prior research work undertaken by Park et al. (2012) and Tamilmani et al. (2019), where it was observed that hedonic features had a strong influence as opposed to utility features. Consequently, and concerning the utility features, individuals can engage a voice assistant to obtain information about a topic or accomplish a task. From the hedonic standpoint, individuals can also utilize digital voice assistants to drive enjoyment and pleasure from interacting with the VA technology.

According to experimental results, social presence significantly influences the perceived value of voice assistants by individuals, thereby corroborating hypothesis H3. Results from the present study align with prior literature from Purington et al. (2017), where the content analysis results on customer reviews of the Amazon brand suggested that a voice assistant was additionally pleasant when customers feel they can socially interact with it. Therefore, VA technology can attract the engagement of individuals with its social presence. Accordingly, it is reasonable to consider that people who perceive a great level of social presence from the VA technology will be more likely to have a more satisfactory experience using it. The results also asserted that the perceived privacy risk (with a high path coefficient value = − 0.308) significantly negatively influences the perceived value of voice assistants by individuals, thereby corrobating hypothesis H4. This discovery is consistent with the previously conducted studies by Lin et al. (2018) and Ford and Palmer (2019), where it was highlighted that the perceived privacy risk strongly and negatively influenced the intention of individuals to adopt intelligent devices. McLean and Osei-Frimpong (2019) also analyzed 724 VAs users and discovered that the perceived privacy risk was an essential aspect hindering the use of speech assistants. Furthermore, Easwara Moorthy and Vu (2015) declared that intelligent personal assistants' users were careful not to disclose their private data to voice assistants and highlighted that privacy risk was an important reason for the non-usage of smart personal assistants. Thus, it is crucial to reduce their privacy risk to promote the constant usage of intelligent personal assistants.

The result of this study supports the notion that individuals believe that irritation has a negative and significant relationship with respect to the perceived worth of digital voice assistants, thereby validating hypothesis H5. However, our findings reveal the difference from a previously conducted study by Lin et al. (2018) where results indicating a very low path coefficient value for irritation and perceived value were obtained. This translates to the fact that the perceived value of VAs will become reduced when consumers experience irritation. The finding also approved that the perceived value positively influences the intention of individuals to use VAs, validating H6. This result supports the findings of Sharma and Klein (2020), which demonstrates that the higher perceived value of an individual user would result in their greater intention to make an online purchase. Furthermore, Hsiao (2013) revealed that the perceived value of possessing access to a mobile Internet service influences the intention of smartphone users to pay for mobile services.

The relationship between the perceived value and individuals' brand loyalty was observed to be significant and positive based on experimental results, confirming hypothesis H7. The literature is also in agreement with the direct association between the perceived value and brand loyalty of users and opines that the perceived value was a significant predictor of consumer loyalty in several settings like telephone services Bolton and Drew (1991), retailing services, and airline travel (Sirdeshmukh et al., 2002). Additionally, our results also back the findings of (Abu ELSamen, 2015; He et al., 2012; Lin et al., 2017), where a significant relationship between perceived value and loyalty, and positive feedback was observed. This study also supports hypothesis H8, which portrays a pronounced and positive association between individuals' perception of voice assistant anthropomorphism and intention to use the service. Our analysis results are consistent with the previously conducted research by Han (2021), which states that consumers' perception of Chabot anthropomorphism will impact their purchase intention of chatbot commerce.

Empirical results also support data regarding the positive and significant influence of perceived intelligence on individuals' behavioral intention to use voice assistants, thus validating hypothesis H9. The obtained result in this study is consistent with the research conducted by Balakrishnan and Dwivedi (2021), which opines that perceived intelligence significantly improves consumers' purchase intention via digital assistants. Also discovered by Tussyadiah and Park (2018), the relationship between the perceived intelligence of robots and the intention of consumers to use hotel service robots was observed to be significant and positive. In addition, McLean et al. (2021) also demonstrated the positive impact of the perceived intelligence of AI voice assistants on customer brand engagement, and contrary to previous research by Islam et al. (2014), the relationship between attractiveness and brand loyalty was insignificant, thereby invalidating hypothesis H10. This finding suggests that a change in the brand appearance and functional performance will impair the visual attractiveness by users and also increase their loyalty to the product.

The results of this study support hypothesis H11, which specifies that the impact of trustworthiness on brand loyalty was significant and positive. Therefore, this result complies with Abbasi et al. (2011), highlighting that trustworthiness specifies the reliability of a product to satisfy customer anticipations and has, therefore, become an essential antecedent of customer loyalty. Thus, in the context of digital voice assistants, trustworthiness must be established by voice assistants, and privacy concerns should reduce to the barest minimum. Trustworthy conditions should be created for consumers to engage their brands and remain loyal to them. Expertise is another factor preceding trustworthiness. The results of the PLS-SEM also indicated that the impact of individual expertise has a positive influence on loyalty toward the brand, validating hypothesis H12. The previous study also confirmed our findings regarding the significant relationship between expertise and consumer loyalty (Bell et al., 2017), and revealed that hypothesis H13 was supported. This hypothesis indicates that the behavioral intention to use voice assistants has a positive impact on brand loyalty.

The moderating influence of brand credibility was further assessed in our model, resulting in the rejection of hypotheses H14a, H14b, H14c, and H14e. This implies that brand credibility does not significantly moderate the relationship between utility features, hedonic features, social presence, irritation, and perceived value. However, our results depict that hypothesis H14d is validated when the perceived brand credibility is high. The findings are consistent with studies conducted by Jain et al. (2022) and Davis et al. (2000), indicating that brands can decrease risk perception, build trust and enhance convenience. Therefore, concerning the moderating role of brand credibility, a significant relationship exists between the perceived privacy risk and perceived value.

Another notable contribution of this research is the examination of the gender variance as a moderator in the proposed model. The results of our analysis reveal that the relationship between utility features and perceived value is insignificant, regardless of the moderating role of gender, thereby invalidating hypothesis H15a. However, our findings reveal that women are more inclined to enjoy the hedonic features of voice assistants than men, as the path coefficients of men – 0.0.146 were lower than that of women – 0.395. This result concurs with other technology investigations Borges et al. (2013), thereby supporting the proposition of hypotheses H15b and H15c. This hypothesis observed the moderating effect of gender to be significant in the association between social presence and perceived value. On the contrary, Jain et al. (2022) demonstrated that women attributed more importance to social presence than men. The findings also revealed a pronounced deviation between men's and women's perception of risk and value by the moderating effects of gender, thus validating hypothesis H15d. This finding does not agree with McLean and Osei-Frimpong (2019), who asserted the absence of significant differentiation in the perception of risks between men and women. Our moderation results for hypothesis H15e showed that gender did not play a significant moderating role in the relationship between irritation and overall perceived value, which resulted in the rejection of the said hypothesis. Finally, by analyzing the moderating role of age between hypotheses H16a to H16e, it was observed that the association between the hedonic features and social presence and perceived value was moderated by age, thus validating hypothesis H16a and H16c. However, the results failed to confirm the moderating impact of age on hedonic features, perceived privacy risk, irritation, and perceived value. Therefore, hypotheses H16b, H16d, and H16e are invalidated.

5.1. Implications for theory

Drawing on the U&GT, signaling, and prospect theories, this study investigated the overall perception and value of voice assistants by consumers and assessed their likeliness to continue using voice assistants. Accordingly, we explored how individuals' perceived value and behavioral intention toward voice assistants influence brand loyalty of voice assistants. The findings of the study recommend several implications for theory and practice, the key contributions which are as follows:

Firstly, to the best of our knowledge, this study is among the first to investigate how brand credibility antecedents such as attractiveness, trustworthiness, and expertise influence the loyalty of consumers to voice assistants. The results of our study indicate the existence of a significant positive relationship between trustworthiness and brand loyalty. Therefore, trust is a notable feature of devices that encourages consumers to express their confidence in the brand and retain long-term relationships. The significant and positive impact of expertise on brand loyalty was also approved in our results. Therefore, if consumers perceive the voice assistant brand as possessing the required expertise and trustworthiness to consistently deliver promises, their loyalty toward the brand will be greatly increased. Additionally, our results revealed that consumers ignored brand attractiveness in their selection of voice assistants.

Further, the results of this study depicted that the privacy risk concerns of consumers supersede the perceived features of voice assistants. Despite the numerous suitable features (utility, hedonic, social presence) of voice assistants, an increasing concern on privacy risks of voice assistants still exists for consumers. Moreover, our findings reaffirm that the relationships established by the U&GT and prospect theories are acceptable and significant. Results reveal that utility and hedonic features, social presence, irritation, and privacy risk were remarkable antecedents for developing consumers' perceived value toward brand loyalty to voice assistants. Our results also indicate that the hedonic features of voice assistants are ranked higher than utility features, thereby contributing to the overall perceived value directed to the continuous use intention.

Taking a cue from signaling theory, the relationship between the perceived privacy risk and perceived value was explored and found to be significantly moderated by brand credibility. Contrary to the findings from the previous study by Jain et al. (2022), the relationship between VA features and their general perceived value was observed to be moderated by brand credibility. However, our results confirmed the significant moderating impact of brand credibility on the existent relationship between the perceived privacy risk and perceived value. Therefore, consumers are willing to decrease their risk perceptions by only opting for brands that have high credibility (Baek, 2007). Thus, it can be concluded that brands positively influence consumer trust, which results in an improved overall value and the continued use of voice assistants.

Numerous scholars have stated that individuals' perceptions of robots' anthropomorphism influence their behavioral intentions as customers (Han, 2021). Our results also demonstrated that the perceived anthropomorphism positively influences the behavioral intention of individuals to use voice assistants. Therefore, consumers tend to only develop significant relationships with VAs when they perceive enjoyment, trust, and anthropomorphism of such devices. Finally, results indicated that the perceived intelligence has a positive impact on the behavioral intention of individuals to use voice assistants. Although some of the studies have backed the statement that perceived intelligence is a fundamental part of AI, its investigation is still essential (Bartneck et al., 2009).

5.2. Implications for practice

This study delivers a holistic model for evaluating the overall perceived value of consumers of voice assistants in China and provides interesting results. For instance, the effect of hedonic features on the perceived value of voice assistants was observed to be more significant than the utility and social presence features of these technologies. Therefore, consumers perceive voice assistants as devices of enjoyment rather than utility, thereby necessitating the need for tech organizations to redefine consumers' perception of those devices. Developers are also urged to ensure that the appearance and performance of the devices are not too human-like to prevent the exhibition of negative attitudes toward them. Developers and researchers should also collaborate toward specifying the ideal levels of anthropomorphism.

The increased concerns of most people are with respect to the trustworthiness of the technology itself and the companies that create them. Since technology requires a massive amount of private data to perform efficiently and consumers can only provide their confidential data when they trust the technology and service provider, trust remains an essential aspect in the adoption of voice assistant technology. Therefore, practitioners must work toward assuring the consumer's trust regarding the security of their confidential information. For instance, organizations should transparently establish data usage and pledge never to sell consumers' data. The perceived privacy risk is another serious concern for consumers' use of voice assistants. Therefore, providers are responsible for undertaking necessary actions to decrease privacy risks for consumers by protecting their interests.

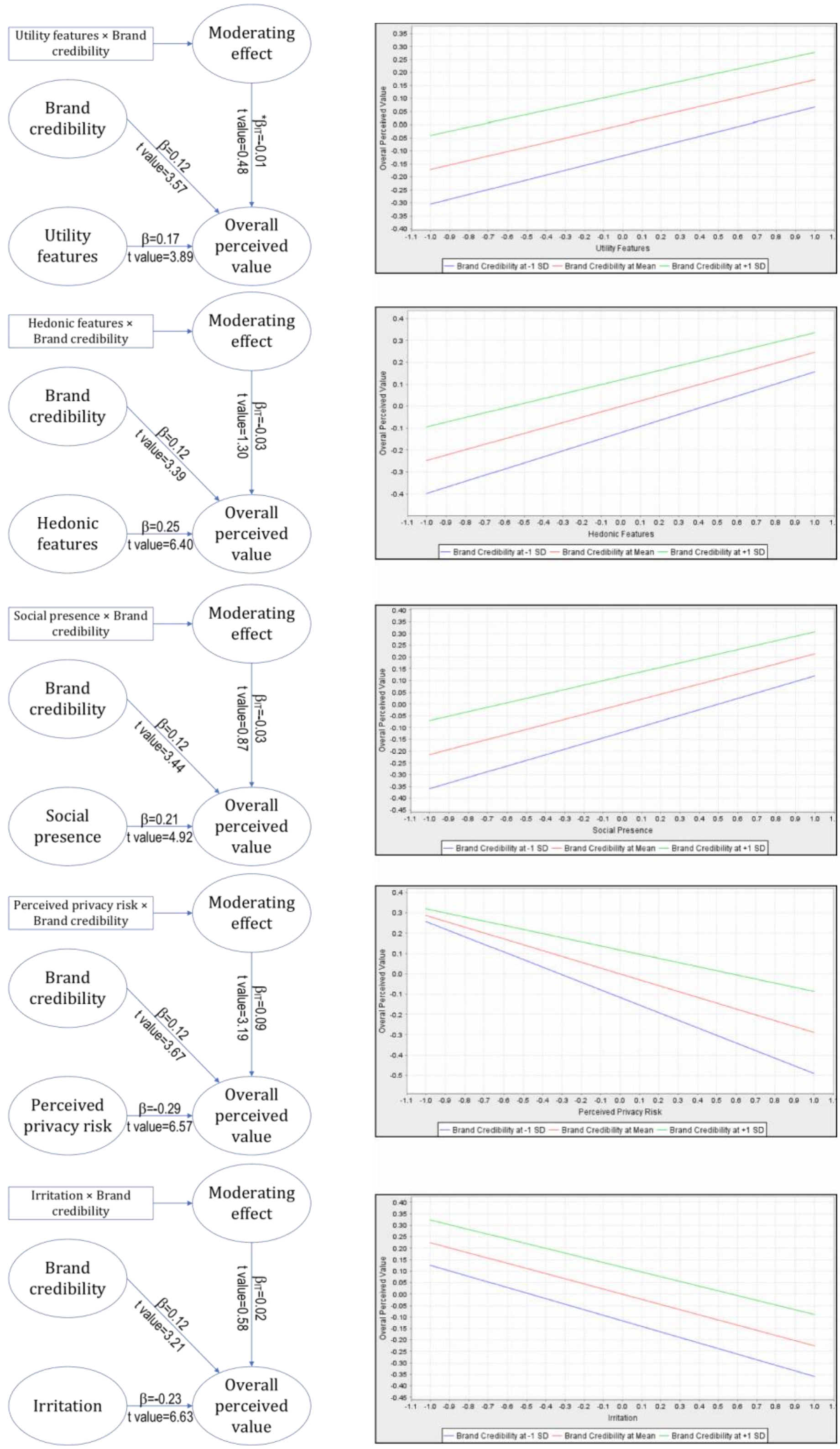
6. Limitations and future directions

There are a few key limitations of this research. This study employed a quantitative method that does not permit an in-depth investigation of consumers' opinions and their intention to use voice assistants. Therefore, qualitative studies could provide richer insights into the experiences and opinions of participants. Future research is also recommended to employ qualitative approaches that offer a deeper understanding of this phenomenon.

This study investigated the moderating impact of brand credibility on voice assistant features and overall value. Future researchers could examine the moderating effect of brand credibility antecedents (attractiveness, trustworthiness, and expertise) between the features of voice assistants and their general worth. Furthermore, the investigation in this study was limited to Alibaba's voice assistant – AliGenie. It would be helpful to test our model with other digital voice assistants to enhance the generalizability of the findings. Lastly, future studies should further evaluate the role of perceived privacy risk. Our findings revealed that the perceived privacy risk is considered the most significant factor of consumers' use of voice assistants. Therefore, future researchers should also examine consumers' concerns with using voice assistants. For instance, via qualitative interviews, researchers may highlight the essential problems of consumers of voice assistants.

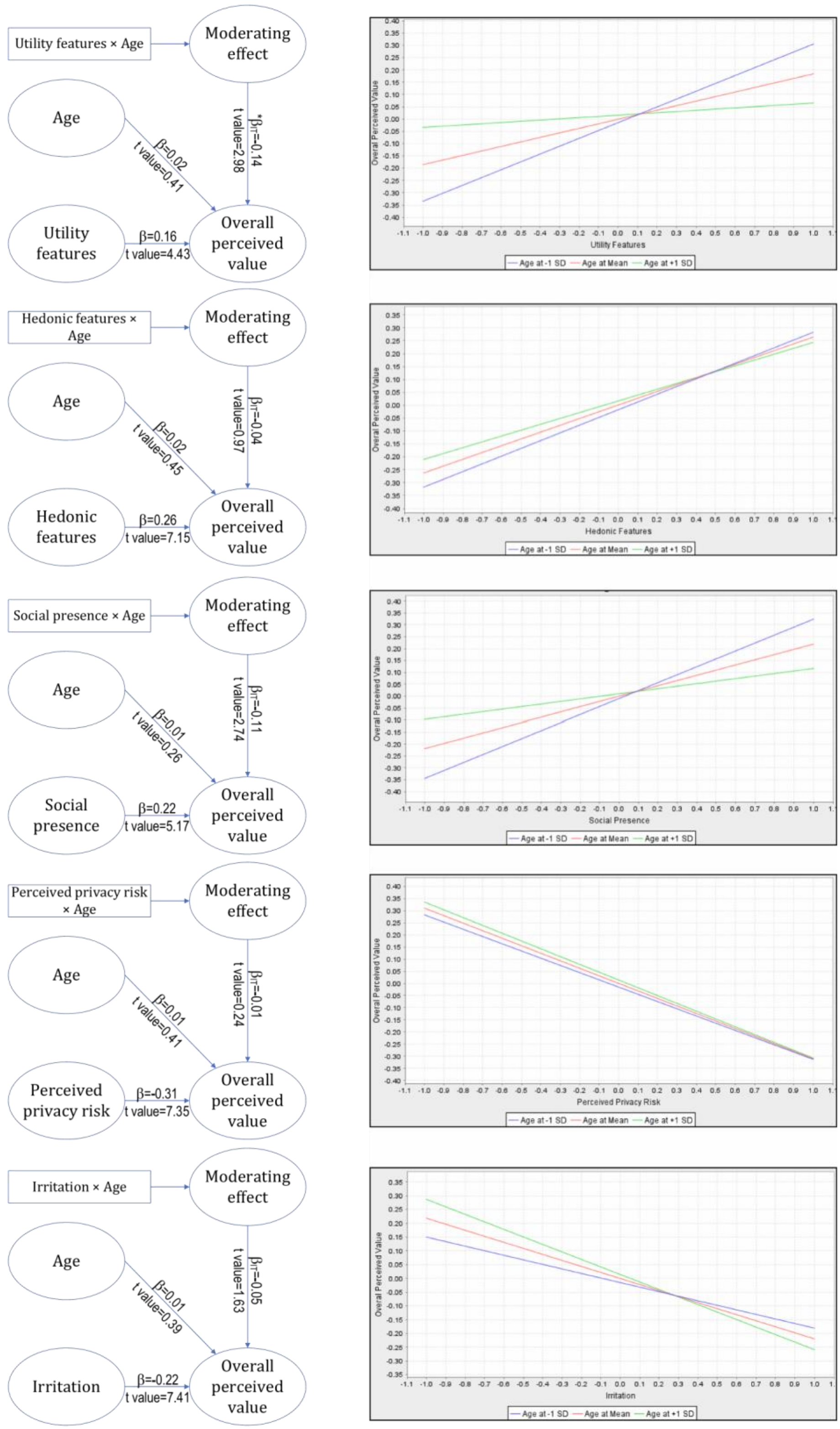
7. Conclusion

The popularity of AI voice assistants is increasing among customers. These technologies help to contribute to the changing interaction between consumers and companies. In this study, a quantitative approach was adopted to investigate the impact of perception and overall perceived value on the behavioral intention of individuals toward the progressive use of voice assistants. The empirical examination revealed that the perceived privacy risk was the most significant factor and obstacle that influenced the general perceived value of consumers to use voice assistants. Moreover, the findings reveal that brand credibility significantly moderates the relationship between the perceived privacy risk and the overall perceived value of voice assistants – an increase in brand credibility results in a decrease in the association between the perceived privacy risk and overall perceived value. Therefore, the influence of perceived privacy risks on the overall perceived value of voice assistants was observed to be negative. The relation between voice assistant features and irritation with the overall perceived value was also observed to be significant. Furthermore, the impact of trustworthiness and expertise on brand loyalty was significant and positive, and finally, empirical results support the positive and significant influence of perceived intelligence and perceived anthropomorphism on the continued usage intention of voice assistants.



*Note: β_{IT}: β for the interaction term.

Fig. A1. Results of assessing the moderating role of brand credibility.



*Note: β_{IT}: β for the interaction term.

Fig. A2. Results of assessing the moderating role of age.

Appendix A
Measuring items for research model.

Constructs	Measurement Items
Utility features	UTF1. In my opinion, using the voice assistant increased my task effectiveness. UTF2. Using the voice assistant enabled me to navigate (browse) quickly. UTF3. In my opinion, using the voice assistant increased my overall efficiency.
Hedonic features	HDF1. I consider that my interaction with the voice assistant is exciting. HDF2. I consider that my interaction with the voice assistant is pleasant. HDF3. I consider that my interaction with the voice assistant is interesting.
Social presence	SCP1. There is a sense of human contact when interacting with the voice assistant. SCP2. There is a sense of personal touch when interacting with the voice assistant. SCP3. There is a sense of sociability when interacting with the voice assistant. SCP4. There is a sense of human warmth when interacting with the voice assistant.
Perceived privacy risk	PPR1. There would be a high potential for privacy loss associated with giving personal information to the voice assistant. PPR2. Personal information could be inappropriately used by the voice assistant service provider. PPR3. Providing my personal information to the voice assistant would involve unexpected problems.
Irritation	IRR1. I believe the voice assistant insults people's intelligence. IRR2. I consider that interaction with the voice assistant is confusing. IRR3. I consider that interaction with the voice assistant is disturbing. IRR4. I believe the voice assistant is not to be trusted.
Overall perceived value	OPV1. I find it easy to get the voice assistant to do what I want it to do. OPV2. The experience with the voice assistant has satisfied my needs and wants. OPV3. Overall, the value of experience with the voice assistant is very high.
Voice assistant continued usage intention	VCU1. I intend to continue using the voice assistant rather than use any alternatives. VCU2. I would like to continue my use of the voice assistant. VCU3. I intend to continue using the voice assistant rather than discontinue its use.
Perceived anthropomorphism	PAP1. The voice assistant functions naturally. PAP2. The voice assistant is conscious of its actions. PAP3. The voice assistant feels lifelike and not artificial.
Perceived intelligence	PCI1. The voice assistant is competent. PCI2. The voice assistant is knowledgeable. PCI3. The voice assistant has intelligent functions. PCI4. The voice assistant is sensible during replies.
Brand loyalty	BRL 1. After using the voice assistance service, I intend to continue using services from this brand. BRL 2. After using the voice assistance service, I consider myself loyal to this brand. BRL 3. After using the voice assistance service, I intend to recommend this brand to others. BRL 4. After using the voice assistance service, I sometimes give others positive feedback about this brand.
Attractiveness	ATR1. I think the voice assistant device is physically attractive. ATR2. I consider the voice assistant very stylish ATR3. I consider the voice assistant very attractive
Trustworthiness	TRW1. I believe that the voice assistant is earnest. TRW2. I feel that the voice assistant is truthful. TRW3. I believe that the voice assistant is trustworthy. TRW4. I feel that the voice assistant is honest.
Expertise	XPR 1. I consider the voice assistant service provider sufficiently experienced in providing digital assistance services. XPR 2. I consider the voice assistant service provider sufficiently expert in providing digital assistance services. XPR 3. I consider the voice assistant service provider competent in providing digital assistance services.

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