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Impact of perceived value on intention to use voice assistants: The moderating effects of personal innovativeness and experience

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Abstract

Voice assistants (VAs), such as Alexa, Siri, and Google Assistant, are instruments increasingly used by consumers to perform daily tasks. The objectives of the present study are to examine the antecedents of consumers' continuance intention to use VAs and the moderating effects of personal innovativeness and experience. Based on behavioral reasoning theory, a research model is proposed to provide insights into the drivers of continuance intention to use. Two empirical studies, based on data collected via online surveys, were conducted. The model was analyzed through partial least squares structural equation modeling. The findings of the studies showed that emotional value and performance expectancy were key antecedents of continuance intention to use, which in turn positively influenced actual use and word-of-mouth intention. In contrast, the quality value was a significant antecedent of continuance intention to use in only one of the two studies, and the influence of price value, social value, effort expectancy, and privacy risk was not found to be significant. However, the second study showed that several of these relationships are moderated by the consumer's experience and personal innovativeness; specifically, less innovative users are sensitive to quality value, and experienced users are sensitive to social value.

KEYWORDS

artificial intelligence, consumer behavior, continuance intention to use, experience, innovativeness, perceived value, smart speaker, voice assistant

1 | INTRODUCTION

In recent years, among the artificial intelligence (AI) applications most used by consumers has been the voice assistant (VA). VAs are software integrated into a variety of platforms, for example, smartwatches, smartphones, and smart speakers (e.g., Amazon Echo), to respond to voice commands given by their users. The most common VAs are Alexa, Siri, and Google Assistant. VA use has increased continuously since their introduction in the early 2010s, and their numbers are expected to exceed the number of humans on earth within a few years; in 2020, 4.2 billion devices were in use, and by 2024 it is expected that this number will double to 8.4 billion (Statista Research Department, 2021).

VAs understand their users' voice instructions and communicate with them using natural language. They can perform a wide variety of tasks, such as playing music and games, provide news and weather reports, make phone calls, operate home automation devices and, even, shop online (Chattaraman et al., 2019). The appeal of VAs lies not only in how well they perform these tasks, but also in the simplicity with which they execute their users' commands, which is due to the VA-user interaction based on the natural language and machine-learning capabilities inherent in the devices. VAs are being designed to become increasingly human-like and to become important parts of their users' daily lives (Hernández-Ortega & Ferreira, 2021). The devices have many benefits, both for companies (e.g., eliciting disclosures from customers, reduced labor costs, operational efficiencies, they learn proactively drawing on multiple information sources) and for users (e.g., convenience, 24/7 service, time-saving, they can be a preferred channel in embarrassing situations, addressing shyness or when discretion is required; Camilleri & Troise, 2023; Mariani et al., 2022). However, the devices also have drawbacks. Castillo et al. (2021) showed that some users in their interchanges with AI technologies had experienced authenticity, cognitive, affective, and functional problems, as well as integration conflicts between the technologies and other customer service channels, which have caused failed service interactions and created dissatisfied customers. Murtarelli et al. (2021) argued that consumers might be wary for cybersecurity reasons, or simply not feel comfortable, conversing with AI-powered agents. Belk (2021) drew attention to a series of ethical dilemmas that might arise for both suppliers and consumers, in particular involving the possibility of being under surveillance 24/7, social engineering, military robots, sex robots, transhumanism and the displacement of human beings and their jobs by AI and robotics.

A significant number of studies have examined consumers' behaviors in their interactions with conversational agents, such as VAs, chatbots, and robots. To date, interest has focused on understanding the determinants of the adoption and use of AI-powered services (Flavián & Casaló, 2021). In this sense, Ling et al.'s (2021) literature review suggested that most studies into intention to use and adopt conversational agents share theoretical foundations based largely on the technology acceptance model (TAM; Davis, 1989) and its subsequent modifications (TAM2 and TAM3), the unified theory of technology use and acceptance (UTAUT; Venkatesh et al., 2003) and the UTAUT2 (Venkatesh et al., 2012). Lim et al. (2022) showed that researchers have used a wide variety of theories, spanning multiple fields (e.g., psychology, sociology, information technology, and communications). For example, Ashfaq et al. (2020) combined the expectation-confirmation model, the information system success model, the TAM and the need for interaction with a service employee to examine consumers' continuance intention to use chatbots; Mamun et al. (2023) applied attachment theory, developed in the social psychology/consumer psychology literature, to explain continuance intention to use VAs; and Belanche et al. (2021) validated a model that assessed to what degree consumers' perceptions of robots' human-like qualities, competence and warmth influenced the service value they expected they would receive and, in consequence, their loyalty.

Some authors have highlighted that research into AI-powered agents has focused mainly on the positive aspects of their interactions with their users, but that more research is required to better understand the effects of their possible costs and drawbacks (e.g., Aw et al., 2022) and on how to mitigate them (Lucia-Palacios & Pérez-López, 2021). In this regard, Belk et al. (2020) questioned whether the value generated by AI-powered agents outweighs the controversial aspects associated with their use. Although recently some studies have drawn particular attention to the positive and negative aspects of the use of these technologies and their effects (e.g., Camilleri & Troise, 2023; Castillo et al., 2021; Mariani et al., 2022), more work is needed to better understand these relationships (Flavián & Casaló, 2021).

While researchers have examined many theories and factors, few, to date, have used behavioral reasoning theory (BRT) (Westaby, 2005) to explain continuance intention to use VAs (Camilleri & Troise, 2023; Ling et al., 2021; Mariani et al., 2022). The main theoretical proposition of BRT is that the consumer's reasons for and against undertaking a given behavior are an important antecedent of his/her intentions. In their review of the marketing-focused AI literature, Mariani et al. (2022) proposed that it would be useful to integrate BRT with other theories of technological acceptance and discussed the reasons for and against the adoption of AI-powered agents. More so than other theories, BRT allows researchers to differentiate between the facilitators of, and barriers to, the adoption and use of technology, adjusting these variables to the specific context of each technology and explaining their impact on consumer behaviors (Westaby, 2005). A detailed examination of the literature revealed that, in the IA context, BRT has been used primarily as a framework to analyze use intention; few studies have employed BRT to analyze the factors that influence continuance intention to use, or to examine the capacity of continuance intention to use to explain recommendation and positive word-of-mouth (WOM) intentions and actual use. WOM plays a critical role in the success of products, services, and technologies, because consumers' intentions to use them depend largely on recommendations made by others (Mishra et al., 2022). Actual use is the only variable that unequivocally reflects user behavior, although researchers often try to explain the intention to use VAs based on its key antecedent role of actual use. However, this relationship pertains only occasionally, when the consumer's behavior is under his/her voluntary control, since most behavior depends, at least to some extent, on non-motivational factors, such as the availability of opportunities and necessary resources (e.g., time, money, and skills) (Ajzen, 1991). In addition, Lalicic and Weismayer (2021) highlighted that many factors, both favorable and unfavorable, can affect the intention to adopt and use AI-powered agents, all of which need to be examined for each technology and in the specific context.

In this sense, in the VA literature, a series of utilitarian and hedonic attributes have been proposed as antecedents of use (see Lim et al., 2022); these do not, however, normally feature the most employed dimensions of perceived value (i.e., quality value, price value, emotional value, and social value) (Sweeney & Soutar, 2001; Zeithaml, 1988). Some researchers have shown that consumer-perceived value is a determining factor in explaining the use of

AI-powered devices (Belanche et al., 2021; Kervenoael et al., 2020). In fact, Loureiro et al. (2021) showed that perceived value (as a second-order construct) is the most influential factor in the quality of tourists' relationships with VAs. In addition, Flavián and Casaló (2021) highlighted the need to increase knowledge of the key factors (focusing on customers, services, technology, etc.) inherent in AI services that influence the customer value creation process, and how to counter risks to privacy. In this sense, Mariani et al. (2022) argued that ethical aspects related to the use of AI, such as privacy, are key issues that have not received enough attention. Similarly, Flavián and Casaló (2021) underlined the need to identify which behavioral differences may arise due to users' characteristics. Previous research has supported the proposal that users' psychographic characteristics (e.g., innovativeness, insecurity, extraversion, and experience) are moderators of their acceptance of AI technologies, due to their effects on the user's ability to adopt disruptive technologies (Belanche et al., 2020), but the analysis of these variables in the context of VAs is very limited.

Given the need to increase knowledge about both the positive and negative factors that influence the use of AI in service industry contexts (Flavián & Casaló, 2021; Mariani et al., 2022), and the importance of understanding how AI creates value for consumers (Flavián & Casaló, 2021), the present study examines the drivers of consumers' continuance intention to use VAs by integrating the BRT and the perceived value paradigm to address the following questions: How do the dimensions of perceived value influence continuance intention to use VAs? How does continuance intention to use influence actual use and intention to transmit positive WOM? Are these relationships moderated by users' psychographic characteristics? To answer these questions, this study explores the influence of six factors/reasons in favor of continuance intention to use, and one factor/reason that does not favor continuance intention. Four of the six factors proposed to a priori favor continuance intention to use correspond to the dimensions of perceived value (quality value, price value, emotional value, and social value; Sweeney & Soutar, 2001), while the other two (effort expectancy and performance expectancy) are among the utilitarian values most frequently featured in studies into conversational agents (Lim et al., 2022; Ling et al., 2021). Privacy risk, one of the factors that most concern users, is proposed as the a priori reason they will not use the devices (Pitardi & Marriott, 2021). In addition, the literature has shown that personal psychographic characteristics, such as personal experience (Fernandes & Oliveira, 2021) and personal innovativeness (Kasilingam, 2020), may influence VA use. Therefore, to increase the knowledge of the strength and directions of the relationships between the aforementioned factors, these two personal characteristics are included in the analysis as possible moderating variables. In summary, the present study extends and enriches BRT by the inclusion of dimensions of perceived value, user expectations, and privacy risk as antecedents of continuance intention to use VAs, which in turn impact on positive WOM and actual use.

With the aim of obtaining consistent results, not dependent on only one sample, we conducted two empirical studies using online surveys. The first study, conducted in 2021, evaluated the relationships between antecedent factors (quality value, price value, emotional value, social value, effort expectancy, performance expectancy, and privacy risk) and continuance intention to use, and the impact of continuance intention to use on intention to transmit positive WOM. The second study, conducted in 2022, replicated the first study to evaluate the consistency of the results, to examine the relationship between continuance intention to use and actual use, and to examine the moderating effects of experience and personal innovativeness on the model's relationships. This two-study design, and the sequence of relationships that were evaluated in each study, were developed taking into account that the first study was carried out at a time when the users' behaviors could still have been influenced by habits acquired during the first two years of the COVID-19 pandemic (2020 and 2021); thus, the decision was made to measure actual use of VAs, and the moderating effects of psychographic characteristics, in the second study.

The present study responds to the calls made in recent systematic literature reviews for further examinations to made of the psychological factors that shape user-conversational agent relationships, and of the impact of privacy risk on continuance intention to use (see Lim et al., 2022; Ling et al., 2021; Mariani et al., 2022). The study's contribution to the literature is as follows. First, the results of the two studies highlight the key role of emotional value and, to a lesser extent, performance expectancy, in the explanation of much of the variance of continuance intention to use. Second, it was shown that quality value is not a consistent driver, as its effect on continuance intention to use was significant only in Study 1. Third, the influence of price value, social value, effort expectancy, and privacy risk on continuance intention to use was not significant; this finding is particularly important because some authors have argued that research into the effects of privacy concerns should be taken further (e.g., Mariani et al., 2022). Fourth, continuance intention to use VAs was seen to strongly influence actual use and intention to transmit positive WOM. Finally, the results of Study 2 help explain these relationships by revealing that, for more experienced users, the social value of VAs discourages continuance intention to use, and that for less innovative users, quality value is a significant driver of continuance intention to use. These findings provide managers with important knowledge of the factors that drive consumers' continuance intention to use VAs that they may draw on to benefit their business strategies.

2 | THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

2.1 | Behavioral reasoning theory

Several authors have suggested that the benefits and costs associated with the use of VAs should be analyzed separately, so that they can be compared, and the acceptance and use of the devices more effectively measured (e.g., Belk et al., 2020; Flavián & Casaló, 2021). Behavioral reasoning theory (Westaby, 2005) argues that the reasons consumers hold for and against a behavior act as antecedents of their motivations to act in particular ways. Reasons have been defined as "specific cognitions connected to a behavioral explanation" (Westaby, 2005, p. 100). Consumers' perceptions of benefits (reasons for) and risks (reasons against) directly affect their reasoning and, consequently, their perceptions of value and intentions to use particular products or services (Lalicic & Weismayer, 2021). Taking these points into account, in the present study BRT is proposed as a valid theory through which to understand the combination of facilitating factors and barriers that influence the use of VAs (Mariani et al., 2022).

While BRT has hitherto been little used to explain consumer behaviors toward VAs (Ling et al., 2021; Mariani et al., 2022), previous studies have demonstrated its usefulness for analyzing the adoption and use of AI-powered devices (e.g., Lalicic & Weismayer, 2021; Lim et al., 2022; Molinillo et al., 2023). There is a need to better understand the specific reasons for, and against, continuance intention to use VAs and their effects on consumers' behaviors, as these reasons may vary between technologies (Lalicic & Weismayer, 2021). Flavián and Casaló (2021) highlighted the need to identify the key factors of value creation, and the privacy risks associated with AI-powered agents. In this sense, Mariani et al. (2022) proposed that it may be possible to combine BRT with other theories, especially technological acceptance theories (e.g., TAM and UTAUT), to improve the explanatory capacity of the behavioral models of AI-powered agent users.

A closer examination of recent studies into VA adoption and use allows us to identify a wide range of variables that could influence continuance intention to use the devices (see Supporting Information, Appendix A). The present study explores the role of seven factors as reasons, or antecedents, of continuance intention to use (or not use) VAs. Possible reasons for this are the four traditional dimensions of perceived value (quality value, price value, emotional value, social value); and two variables from the UTAUT (effort expectancy and performance expectancy), attributes of the technology that clearly have a strong influence on consumer behaviors (see Aw et al., 2022). A possible key reason against use is privacy risk (Kronemann et al., 2023), the effects of which should be further studied (Mariani et al., 2022).

2.2 | Perceived value

Perceived value is an overall assessment of the usefulness of a product based on the customer's perceptions of its benefits and costs (Zeithaml, 1988). This variable is widely considered to be one of the best predictors of behavioral intentions, including predicting the intention to continue using a technology (Singh et al., 2021). Although perceived value was omitted from initial technology adoption theories, various authors (e.g., Belanche et al., 2021; Kervenoael et al., 2020) have argued that consumer perceived value is a key variable in the understanding of the cognitive reactions of users which lead them to use AI-powered technologies.

Continuance intention to use a technology reflects intended future consumption, or use, which is closely related to actual use (Hernández-Ortega & Ferreira, 2021). Continuance intention differs from intention to use a technology, such as VAs, for the first time, because repeated experiences provide the user with information and expectations (Loureiro et al., 2021). Consequently, various authors (e.g., Han & Yang, 2018) have argued that continuance intention to use is a key construct in understanding the use of information systems and, in particular, VAs (Hernández-Ortega & Ferreira, 2021).

Recent studies have shown that perceived value, measured one-dimensionally, influences VA users' behavioral intentions (Lalicic & Weismayer, 2021; Maroufkhani et al., 2022). However, some researchers in the VA field have used multidimensional conceptualizations (e.g., Loureiro et al., 2021). In this sense, one of the perceived value measurement scales most frequently used in the literature is that of Sweeney and Soutar (2001), who argued that perceived value is a construct with four distinct value dimensions: quality value, price value, emotional value, and social value. In the context of VAs, quality value reflects the utility that users expect will be derived from the quality, design, and operation of the device; price value refers to value for money, that is, the utility that the user perceives (s)he gains from advantages inherent in some technologies that make it cheaper to access some services (over the access provided by other technologies); social value is the utility derived from the ability of the product, service or technology to enhance the user's social self-concept; and emotional value reflects the usefulness of the device based on the feelings or affective state it generates (Belanche et al., 2021; Singh et al., 2021; Sweeney & Soutar, 2001).

Zeithaml (1988) argued that perceived value is a primary customer motivation for buying or using a product or service. In the VA field, Loureiro et al. (2021) demonstrated that perceived value positively influences the quality of the relationship between the consumer and the device, while Jain et al. (2022) and Maroufkhani et al. (2022) showed that it is a key antecedent of continuance intention to use. In Loureiro et al. (2021), perceived value was measured as a second-order, 4-dimensional (quality value, price value, emotional value, and social value) construct, while in Jain et al. (2022) and Maroufkhani et al. (2022), it was measured as a one-dimensional construct. Belanche et al. (2021) demonstrated that three of the four perceived value dimensions referenced above significantly influence continuance intention to use conversational agents (i.e., robots). Hence, the following hypotheses are proposed:

H1 Perceived quality value positively influences continuance intention to use voice assistants.

H2 Perceived price value positively influences continuance intention to use *voice assistants*.

H3 Perceived emotional value positively influences continuance intention to use *voice assistants*.

H4 Perceived social value positively influences continuance intention to use *voice assistants*.

2.3 | Effort and performance expectancy

In addition to the four dimensions of perceived value, the literature identifies other reasons/factors that positively influence intention to use AI-powered devices, among the more important of which are the two utilitarian attributes of effort expectancy and performance expectancy (Lim et al., 2022; Ling et al., 2021; Mariani et al., 2022). Effort expectancy is the degree of ease that consumers associate with using technology. Previous studies have shown that effort expectancy (or ease of use) has a positive influence on intention to use new technologies. Most studies have found that, if a technology is easy to use, or involves low effort, intention to use it will be reinforced. For example, Kervenoael et al. (2020) concluded that ease of use indirectly affects intentions to use social robots. In the VA field, Pitardi and Marriott (2021) demonstrated that ease of use indirectly influences, through attitude and confidence, intention to use, and Coskun-Setirek and Mardikyan (2017) and Vimalkumar et al. (2021) showed that a positive, direct influence exists between effort expectancy and intention to use. Therefore, the following hypothesis is proposed:

H5 Perceived effort expectancy positively influences continuance intention to use *voice assistants*.

Performance expectancy has been defined as the extent of users' beliefs in the benefits that a technology will bring them (e.g., utility, efficiency, and productivity) in the performance of certain activities (Venkatesh et al., 2012). There is a broad consensus that if consumers perceive that the use of a technology will bring benefits, their intention to use it will increase (Venkatesh et al., 2012). Nonetheless, performance expectancy depends on the purpose to which the technology is put, and the context, thus its impact must be examined in all relevant areas (Moriuchi, 2019). In the context of VAs, several studies have demonstrated the positive impact of performance expectancy on consumers' perceptions. Moriuchi (2019) showed that perceived usefulness influences consumers' attitudes towards, and engagement with, VAs. Pitardi and Marriott (2021) showed that performance expectancy exerted indirect effects on intention to use, through attitude toward the devices, while Jain et al. (2022) and Maroufkhani et al. (2022) demonstrated that it positively influences continuance intention to use VAs through perceived overall value. Coskun-Setirek and Mardikyan (2017) and Vimalkumar et al. (2021) confirmed that a direct, positive relationship exists between performance expectancy and intention to use VAs. Thus, it is hypothesized that:

H6 Perceived performance expectancy positively influences continuance intention to use *voice assistants*.

2.4 | Privacy risk

The privacy risk literature mainly focuses on users' concerns about losing control of their personal information (Vimalkumar et al., 2021). Achieving privacy of user information is one of the most important challenges faced in driving the adoption and use of VAs (Mariani et al., 2022). VAs can undertake many tasks at users' requests and, depending on the permissions granted to them by their users, can store sensitive, private user data, such as browsing history, contacts, agenda, and purchases, and listen continuously, ready to be activated with their keyword (e.g., "Alexa," "Hi Google"), and can send recordings to the manufacturer. Several studies have noted that consumers are aware of these VA characteristics. In a study into consumers' adoption of voice technologies and digital assistants, 52% of participants stated that their main concern about VAs is that their personal information/data is not secure (Olson & Kemery, 2019). Perceived privacy risk has been defined, in the VA context, as users' fears that third parties might gain unauthorized access to, and potentially misuse, personal data held by their VAs (Han & Yang, 2018).

Previous research has shown that perceptions of privacy risk can influence users' attitudes and behaviors toward VAs (Kronemann et al., 2023). For example, it has been shown that perceptions of privacy risk reduce perceived utility (Lucia-Palacios & Pérez-López, 2021), perceived value (Jain et al., 2022; Maroufkhani et al., 2022), trust in VAs (Vimalkumar et al., 2021), loyalty toward the VA brand (Hasan et al., 2021), emotional affinity with the VA (Han & Yang, 2018) and attitudes toward the VA (Pitardi & Marriot, 2021). In addition, studies in other areas have shown that perceptions of privacy risk can reduce the intention to use mobile payments (Slade et al., 2015), among other technologies. Therefore, the following hypothesis is proposed:

H7 Perceived privacy risk negatively influences continuance intention to use *voice assistants*.

2.5 | Word-of-mouth

WOM is one of the most examined outcome variables in the AI field. As to VAs, their emergence and novelty mean that many users do not fully understand the operation of the technology (Maroufkhani et al., 2022); thus, they seek information from people similar to themselves. In this sense, some works, such as Mishra et al. (2022), showed that users' attitudes, both utilitarian and hedonic, had positive effects on their intention to recommend VAs. Hernández-Ortega and Ferreira (2021) concluded that intention to transmit positive WOM and continuance intention to use VAs are closely related constructs, and indications of the loyalty of the consumer toward the service. Similarly, Maroufkhani et al. (2022) showed that continuance intention to use VAs has a positive impact on users' loyalty toward the VA brand. Thus, when users demonstrate an intention to continue using VAs, they will also recommend them to other people. Consequently, we propose the following hypothesis:

H8 Continuance intention to use *voice assistants* positively influences users to transmit positive word-of-mouth about *voice assistants*.

2.6 | Actual use

Consumers' behavioral intentions have been used in traditional technology adoption theories (TRA, TPB, TAM, etc.) as the key predictors of consumers' actual behaviors (e.g., Venkatesh et al., 2012). Behavioral intentions are individuals' intentions to act on, or continue to act on, a decision previously taken, leading them to take the relevant action (Ajzen, 1991). Previous studies (e.g., Coskun-Setirek & Mardikyan, 2017) in the VA field have shown that intention to use can help explain actual use. Thus, it is proposed that continuance intention to use a VA is a necessary precursor for the user to actually use it in a sustained, and frequent way, over time (Jain et al., 2022). Therefore, the following hypothesis is proposed:

H9 The actual use of *voice assistants* is positively determined by continuance intention to use the devices.

2.7 | Moderating personal characteristics: Personal innovativeness and experience

The literature has shown that users' personal characteristics can moderate their intention to use a new technology (Venkatesh et al., 2003). The adoption of technological innovations depends on the ability of users to deal with the innovation (Belanche et al., 2020; Flavián et al., 2023). The present study analyses the moderating effect of two psychographic characteristics, personal innovativeness, and experience. These two characteristics are related to technology readiness, one of the main user characteristics that condition the use of new technologies (Belanche et al., 2020). In this sense, it is expected that users with higher levels of personal innovation (Jeong et al., 2009) and more experience of new technologies (Liébana-Cabanillas et al., 2014) will have a more positive perception of the technologies and greater continuance intention to use them and, a posteriori, will recommend and use them more than other users (Jianlin & Qi, 2010).

Personal innovativeness is a personality trait that reflects the degree to which an individual is open to experimenting with new technologies (Slade et al., 2015). Innovators are individuals open to trying new technologies, who want to absorb information and to search for new trends, who perceive less risk in using technologies, and who feel a greater sense of control and self-confidence over their actions (Acikgoz et al., 2022). Empirical studies have demonstrated the influence of personal innovativeness on consumer perceived value and intention to use new technologies, such as e-commerce (Jackson et al., 2013), mobile payment systems, and biometric payment systems (Liébana-Cabanillas et al., 2022). In the context of VAs, Hasan et al. (2021) showed that the effect of novelty value on brand loyalty is greater among more innovative consumers. The present study explores the moderating effect of personal innovativeness on the relationships of the proposed model. While insufficient evidence exists to unequivocally establish the direction of moderation, from the review of the literature on adoption and use of technologies, it is proposed that personal innovativeness will strengthen the model's relationships. Therefore, we propose the following:

P1 Personal innovativeness reinforces the positive effect of (1) quality value, (2) price value, (3) emotional value, (4) social value, (5) effort expectancy and (6) performance expectancy, and reduces the negative effect of (7) privacy risk, on continuance intention to use, while increasing the effect of continuance intention to use on (8) positive WOM intention and (9) actual use.

Earlier technology adoption studies have suggested that the user's previous experience plays an important role in technology acceptance, as the more experience (s)he has, the more likely (s)he will be to have relevant knowledge, skills, and confidence, and the less likely (s)he will be to feel anxiety when interacting with technologies (Fernandes & Oliveira, 2021). The previous knowledge that consumers possess of technologies influences their behaviors, as it conditions their perceptions of the information they will need to perform specific actions (Acikgoz et al., 2022) and, therefore, the resources and capabilities they will require. Consequently, a lack of relevant experience and knowledge creates major barriers to the adoption of new technologies (Slade et al., 2015).

Fernandes and Oliveira (2021) demonstrated that the functional, social, and relational characteristics of VAs have more impact on VA acceptance among consumers who use them more frequently. Chattaraman et al. (2019) showed that the more experience older people have of technologies, the more benefits they derive from their VAs. However, other works have questioned the direction of the moderating effect of experience. For example, Loureiro et al. (2021) found that the level of the user's technological expertise weakens the effects of perceived value on the relationship quality (i.e., satisfaction, commitment, and trust) between users and their VAs. In the present study, it is proposed that the user's level of experience in the use of VAs moderates the relationships of the research model and, although insufficient supportive evidence exists to be definitive, it is proposed that a higher level of experience will increase the positive relationships and decrease the negative relationships between the variables of the proposed model. Therefore, the following proposition is made:

P2 The user's level of experience with *voice assistants* reinforces the positive effects of (1) quality value, (2) price value, (3) emotional value, (4) social value, (5) effort expectancy and (6) performance expectancy, and reduces the negative effects of (7) privacy risk, on continuance intention to use, while increasing the effects of continuance intention to use on (8) positive WOM intention and (9) actual use.

The conceptual model of the research is shown in Figure 1.

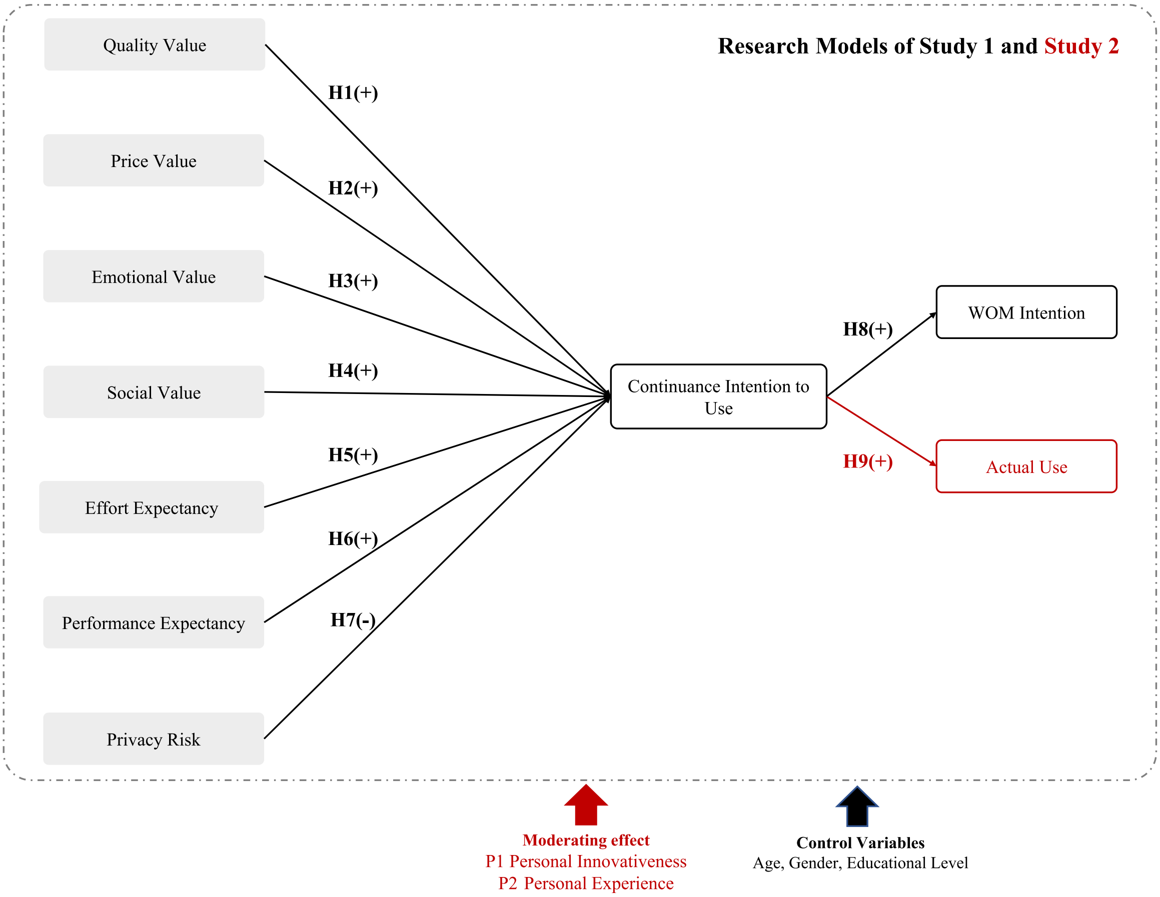

FIGURE 1 Conceptual model.

3 | STUDY 1: ANTECEDENTS OF CONTINUANCE INTENTION TO USE

3.1 | Sample and measurements

The first study explored the effects of the proposed antecedents (see Figure 1) on continuance intention to use VAs, and of this on intention to transmit positive WOM. Thus, the study focuses on experienced users. The data were collected in October 2021, through a structured online questionnaire, from a sample of Spanish VA users following a non-probability sampling procedure. To reduce possible biases, the link to the questionnaire was distributed through various email lists and social networks. In their invitation to take part in the study, the participants received a description of its objectives and had to provide consent to their voluntary participation. The survey asked questions about the participants' use of VAs, the main variables of the study, and their sociodemographics. A filter question ensured that only people with VA experience took part. The participants answered the questions based on their previous experience with the VAs they use most. At the end of the survey, the participants were invited to share the questionnaire with contacts who had previous VA experience. Responses that were deemed invalid, and repeat responses, were discarded.

In total, we collected 345 responses, of which 184 came from experienced VA users. The sample size significantly exceeds the minimum suggested by Hair et al. (2017) for a PLS-SEM analysis, and showed sufficient power, as verified by a power analysis based on the heuristic standards of Cohen's tables and the square root method, and subsequently verified with G*Power. In terms of representativeness, the majority (63%) were young people between 18 and 24 years, a demographic segment very active in the use of VAs, and 10.9% were between 45 and 54 years (Flavián et al., 2023; Hernández-Ortega & Ferreira, 2021); 59.24% were women. Most (58.15%) respondents claimed to have an average level of VA experience. The most common uses they made of their VAs were streaming music (39.1%), checking weather forecasts (34.2%), making telephone calls (31.9%), and answering general knowledge questions (23.5%). The most used VAs were Siri (40.8%), Google Assistant (36.8%), and Alexa (18.8%).

The scales used to measure the model's variables were adapted from previous studies (Table 1). The dimensions of perceived value (quality value, price value, emotional value, and social value) were adapted from Sweeney and Soutar (2001). Effort expectancy and performance expectancy were measured through an adaptation of the scales proposed by Venkatesh et al. (2012). Perceived privacy risk was measured through the adaptation of a scale proposed by McLean

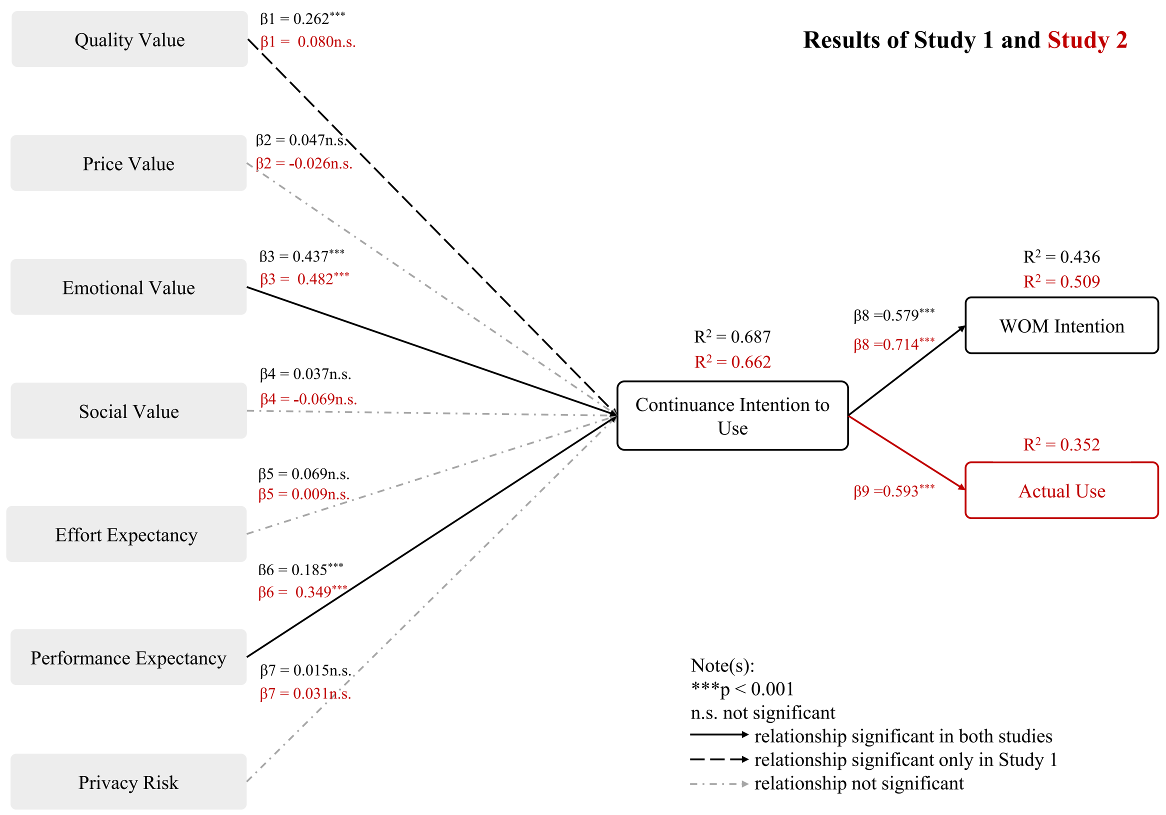

FIGURE 2 Results of the structural model assessment.

and Osei-Frimpong (2019), continuance intention to use by a scale adapted from Venkatesh et al. (2012), and WOM by a scale proposed by Hernández-Ortega and Ferreira (2021). In all cases, 7-point Likert scales were used (1 = "strongly disagree"; 7 = "strongly agree").

3.2 | Measurement model assessment: Reliability and validity

To ensure that the correlations between the variables were not significantly influenced by the measurement instrument employed, common-method bias (CMB) was evaluated using Harman's single-factor test. The results indicated that the total variance for any one single factor was less than 40.03% and, therefore, less than the maximum recommended value (50%). As Harman's single-factor test has some limitations (Podsakoff et al., 2003), a second method, used to test CMB with PLS, was followed, employing a procedure that compares inter-construct correlations (Pavlou et al., 2007). The highest correlation in the correlation matrix was $r = 0.769$ (Study 1) and $r = 0.788$ (Study 2); the presence of CMB would have produced extremely high correlations ($r > 0.90$). In addition, the full collinearity assessment approach, proposed by Kock (2015), was taken to assess whether CMB was present. The results showed that all variance inflation factors (VIFs) in the internal model, used to detect the existence of collinearity or correlation among the independent variables, were equal to, or less than, 3.3 (and below the maximum threshold of 5), which indicates that they were free from CMB. Consequently, it is reasonable to conclude that CMB did not significantly influence the results of the study. To evaluate the proposed model, the data, due to the small sample size, were analyzed through partial least squares structural equation modeling (PLS-SEM; Hair et al., 2019), using Smart PLS 4.0.8 software.

The PLS-SEM technique is particularly suitable for exploring relationships not previously examined in other empirical studies, as is the case with the relations and moderating effects in the proposed model. In addition, PLS-SEM can handle latent constructs under non-normal conditions and requires less restrictions on sample size and residue distribution (Hair et al., 2017). To ensure consistency of results, we implemented the consistent version of PLS (PLSc), which allowed us to address inconsistencies associated with the traditional PLS method, such as erroneous estimates of construct routes and measurements (Dijkstra & Henseler, 2015).

A two-stage process was followed: first, the measurement model (the reliability and validity of the measurements) was evaluated and, thereafter, the structural model was evaluated (hypotheses testing; Hair et al., 2019).

Reliability was analyzed using Cronbach's alpha (CA) and composite reliability (CR) indices. The values of the indices were greater than 0.60 (Table 1), so reliability is confirmed (Hair et al., 2019). Convergent validity was assessed using average variance extracted (AVE; Fornell & Larcker, 1981). The AVE values were higher than the recommended minimum (0.50; Table 1), so

TABLE 1 Descriptive statistics, reliability, and convergent validity.

Constructs and items	Study 1 ($n1 = 184$)						Study ($n2 = 230$)					
	FL	M	SD	CA	CR	AVE	FL	M	SD	CA	CR	AVE
Quality Value (QV)				0.762	0.842	0.523				0.841	0.885	0.582
QV1.	0.770	4.293	1.230				0.875	5.235	1.438			
QV2.	0.834	4.758	1.049				0.884	5.574	1.339			
QV3.	0.770	4.932	0.991				0.849	5.687	1.226			
QV4. (R)	0.510	3.885	1.368				0.686	4.630	1.926			
QV5. (R)	0.687	3.683	1.393				0.284	4.039	1.957			
QV6.	0.770	4.731	1.077				0.819	5.535	1.250			
Price Value (PV)				0.895	0.927	0.761				0.938	0.956	0.844
PV1.	0.889	4.400	1.235				0.924	5.265	1.415			
PV2.	0.876	4.451	1.166				0.940	5.370	1.373			
PV3.	0.892	4.345	1.222				0.946	5.352	1.390			
PV4.	0.832	4.014	1.348				0.862	3.791	1.067			
Emotional Value (EV)				0.883	0.915	0.682				0.932	0.948	0.786
EV1.	0.835	4.195	1.257				0.888	5.313	1.698			
EV2.	0.806	4.309	1.377				0.884	5.239	1.719			
EV3.	0.814	4.203	1.268				0.874	5.343	1.569			
EV4.	0.844	3.993	1.356				0.899	5.004	1.738			
EV5.	0.829	4.175	1.340				0.888	4.935	1.794			
Social Value (SV)				0.857	0.900	0.694				0.967	0.976	0.909
SV1.	0.772	3.490	1.401				0.952	3.604	2.182			
SV2.	0.812	3.701	1.356				0.956	3.496	2.202			
SV3.	0.851	3.717	1.327				0.952	3.783	2.138			
SV4.	0.891	3.731	1.449				0.955	3.678	2.197			
Effort Expectancy (EE)				0.860	0.904	0.703				0.912	0.938	0.792
EE1.	0.766	5.101	1.099				0.840	6.135	1.188			
EE2.	0.831	4.764	1.161				0.889	5.717	1.326			
EE3.	0.859	5.027	1.069				0.904	5.943	1.276			
EE4.	0.894	4.894	1.140				0.924	6.009	1.275			
Performance Expectancy (PE)				0.677	0.804	0.508				0.874	0.914	0.726
PE1.	0.795	3.583	1.173				0.886	5.665	1.440			
PE2.	0.688	4.616	1.260				0.840	5.026	1.801			
PE3.	0.702	4.283	1.298				0.822	5.913	1.421			
PE4.	0.659	4.256	1.200				0.860	5.683	1.402			
Privacy Risk (PR)				0.705	0.819	0.531				0.770	0.853	0.659
PR1.	0.685	4.582	1.248				0.866	5.239	1.729			
PR2.	0.693	4.477	1.327				0.804	5.578	1.801			
PR3.	0.785	4.487	1.315				0.762	5.335	1.731			
Continuance Intention to Use (CIU)				0.875	0.914	0.728						
CIU1.	0.815	4.553	1.214				0.874	5.696	1.378			

TABLE 1 (Continued)

	Study 1 (n1 = 184)						Study (n2 = 230)					
Constructs and items	FL	M	SD	CA	CR	AVE	FL	M	SD	CA	CR	AVE
CIU2.	0.871	3.971	1.331				0.907	5.222	1.774			
CIU3.	0.872	4.248	1.362				0.947	5.426	1.640			
CIU4.	0.853	4.312	1.339				0.936	5.504	1.582			
Word-of-Mouth Intention (WOM)				0.869	0.919	0.792				0.935	0.958	0.885
WOM1.	0.893	4.315	1.176				0.949	5.370	1.468			
WOM2.	0.909	4.266	1.206				0.947	5.326	1.539			
WOM3.	0.867	4.158	1.326				0.925	5.139	1.719			
Personal Innovativeness (PI)	-	-	-	-	-	-				0.897	0.928	0.763
PI1.	-	-	-	-	-	-	0.843	3.957	2.160			
PI2.	-	-	-	-	-	-	0.863	4.600	2.025			
PI3.	-	-	-	-	-	-	0.914	4.970	1.814			
PI4.	-	-	-	-	-	-	0.872	5.061	1.768			
Actual Use (AU)							1	3.726	1.653			
Personal Experience (PEX)	-	-	-	-	-	-	1	2.391	0.810			

Abbreviations: AVE, average variance extracted; CA, Cronbach's alpha; CR, composite reliability; FL, factor loading; M, mean; SD, standard deviation; R, reverse scored.

convergent validity is confirmed. Discriminant validity was assessed using two methods: first, a test of whether the inter-construct correlations between variables were less than the value of the square roots of the AVEs (Fornell & Larcker, 1981) and, second, whether the heterotrait-monotrait (HTMT) ratio between any two reflective constructs was below 0.90 (Henseler, Hubona, et al., 2016). All values were consistent with the recommended limits (Table 2); therefore, the measurement model has discriminant validity.

3.3 | Structural model assessment and hypotheses testing

The results of the structural model analysis are shown in Table 3. To test the hypotheses, the values of the β coefficients and p-values of each regression were assessed.

Perceived quality value significantly and positively influenced continuance intention to use VAs ($\beta1 = 0.262$, $t = 4.267$, $p < 0.001$), providing support for H1. Perceived emotional value had a significant and positive effect on continuance intention to use VAs ($\beta3 = 0.437$, $t = 6.128$, $p < 0.001$), supporting H3. Perceived performance expectancy significantly and positively impacted on continuance intention to use VAs ($\beta6 = 0.185$, $t = 3.079$, $p < 0.001$), confirming H6. In turn, continuance intention to use had a significant and positive influence on positive WOM intention ($\beta8 = 0.579$, $t = 10.671$, $p < 0.001$), supporting H8. On the other hand, perceived price value ($\beta2 = 0.047$, $p > 0.1$) (H2), perceived social value ($\beta4 = 0.037$, $p > 0.1$) (H4), perceived effort expectancy ($\beta5 = 0.069$, $p > 0.1$) (H5) and perceived privacy risk ($\beta7 = 0.015$, $p > 0.1$) (H7) did not significantly impact on continuance intention to use VAs.

The R^2 values indicate that the model explains 68.7% of the variance of continuance intention to use VAs and 43.6% of intention to transmit positive WOM. The f^2 values were used to assess effect size: values above 0.35, 0.15, and 0.02 are considered strong, moderate, and weak, respectively (Henseler, Hubona, et al., 2016). To evaluate the predictive capacity of the structural model, Q^2 values were calculated through a blindfolding procedure/Stone-Geisser test. The Q^2 value for continuance intention to use was 0.497, and for intention to transmit positive WOM was 0.306.

To determine if sociodemographic factors had influenced the results of the research model, gender, age, and educational level were applied as control variables, using a bootstrapping procedure, with 5000 subsamples (see Table 3). This analysis found they had no significant effects in either the measurement or structural model.

3.4 | Discussion of Study 1

The results indicate that the value perceived by users plays an important role in continuance intention to use VAs. In particular, it was shown that users place importance on value, above all, emotional value and, to a lesser extent, quality value. The results also showed that performance expectancy is an important variable in the explanation of continuance intention to use. Therefore, it can be said that pleasure, the affective state derived from using VAs, and the usefulness of VAs for performing certain tasks, are the factors that most influence users' continuance intentions to use the devices.

Conversely, neither price value nor social value was shown to have a significant influence on continuance intention to use. Regarding price,

TABLE 2 Discriminant validity of the measures.

	Study 1								
Constructs	CIU	EE	EV	QV	PE	PV	PR	SV	WOM
1. Continuance Intention to Use (CIU)	*0.853*	0.324	0.756	0.695	0.596	0.528	0.185	0.290	0.659
2. Effort Expectancy (EE)	0.287	*0.839*	0.408	0.541	0.473	0.315	0.116	0.107	0.188
3. Emotional Value (EV)	0.669	0.364	*0.826*	0.669	0.543	0.603	0.160	0.365	0.558
4. Quality Value (QV)	0.574	0.436	0.551	*0.723*	0.519	0.618	0.241	0.274	0.562
5. Performance Expectancy (PE)	0.462	0.363	0.420	0.382	*0.713*	0.425	0.303	0.238	0.567
6. Price Value (PV)	0.467	0.281	0.538	0.513	0.335	*0.873*	0.205	0.277	0.395
7. Privacy Risk (PR)	0.136	0.028	0.114	0.148	0.198	0.154	*0.747*	0.179	0.196
8. Social Value (SV)	0.269	0.082	0.323	0.226	0.151	0.236	0.129	*0.833*	0.345
9. Word-of-Mouth Intention (WOM)	0.578	0.169	0.490	0.467	0.437	0.350	0.126	0.296	*0.890*

	Study 2									
Constructs	AU	CIU	EE	EV	PE	PR	QV	SV	PV	WOM
1. Actual use (AU)	*1*	0.624	0.343	0.475	0.554	0.056	0.424	0.086	0.317	0.438
2. Continuance Intention to Use (CIU)	0.624	*0.871*	0.589	0.832	0.818	0.083	0.724	0.350	0.599	0.775
3. Effort Expectancy (EE)	0.344	0.586	*0.850*	0.614	0.642	0.103	0.662	0.188	0.530	0.492
4. Emotional Value (EV)	0.477	0.833	0.615	*0.855*	0.793	0.095	0.839	0.539	0.708	0.793
5. Performance Expectancy (PE)	0.555	0.815	0.640	0.790	*0.799*	0.126	0.706	0.389	0.643	0.733
6. Privacy Risk (PR)	0.050	0.090	0.080	0.098	0.122	*0.691*	0.063	0.176	0.131	0.104
7. Quality Value (QV)	0.423	0.722	0.665	0.834	0.700	0.031	*0.781*	0.384	0.806	0.797
8. Social Value (SV)	0.086	0.353	0.190	0.536	0.386	0.190	0.369	*0.938*	0.377	0.463
9. Price Value (PV)	0.320	0.599	0.531	0.706	0.640	0.129	0.796	0.375	*0.893*	0.749
10. Word-of-Mouth Intention (WOM)	0.437	0.774	0.493	0.792	0.729	0.080	0.787	0.462	0.744	*0.910*

Note. The square roots of the AVEs are in italics on the main diagonal. The Fornell-Larcker criterion is depicted below the main diagonal. The heterotrait-monotrait (HTMT) ratio of correlations is above the main diagonal.

this result may be due to the fact that VAs usually come incorporated into devices with multiple functions (e.g., Siri on a MacBook computer), thus making them difficult to cost, or because ad hoc devices are relatively cheap compared to other technological devices (e.g., Amazon Echo). As to social value, the result may be due to the fact that VAs are so easy to use and so accessible that their users do not believe that they help them project a certain image of themselves; thus, they will not enhance the perceptions that others have of them.

Similarly, the results did not show that effort expectancy and perceived privacy risk have a significant effect on continuance intention to use the devices. Regarding effort expectancy, this may be because the effort required to use VAs is very low due to their ease of use and their natural language-supported voice interaction function. The results showed that users do not regard privacy risk as significant, either because they believe that the risk does not hold consequences for them, or because they believe that the probability of harm occurring is very low compared to the benefits provided by VAs.

Finally, continuance intention to use VAs is a very important factor in the explanation of intention to transmit positive WOM. This result suggests that users who want to continue using these devices want to share their experiences with others so that they, in turn, can enjoy similar benefits.

4 | STUDY 2: ACTUAL BEHAVIORS AND MODERATORS

4.1 | Sample and measurements

The objectives of the second study are to replicate Study 1 while expanding the model by incorporating the dependent variable actual use, and to examine the moderating effects of personal innovativeness and experience. The data collection procedure, conducted in October 2022, was similar to that used in Study 1. The 230 participants were principally

TABLE 3 Results of the hypotheses testing.

		Study 1			Study 2			
Hypotheses	Relationships	β	f^2	t Value	β	f^2	t Value	Results
H1	Quality Value → Continuance Intention to Use	0.262	0.174	4.267***	0.080	0.007	0.915 ns	Partially Supported
H2	Price Value → Continuance Intention to Use	0.047	0.002	0.691 ns	−0.026	0.001	0.229 ns	Not Supported
H3	Emotional Value → Continuance Intention to Use	0.437	0.306	6.128***	0.482	0.188	5.273***	Supported
H4	Social Value → Continuance Intention to Use	0.037	0.001	0.683 ns	−0.069	0.011	1.718 ns	Not Supported
H5	Effort Expectancy → Continuance Intention to Use	−0.069	0.058	1.456 ns	0.031	0.002	0.474 ns	Not Supported
H6	Performance Expectancy → Continuance Intention to Use	0.185	0.123	3.079***	0.349	0.156	4.979***	Supported
H7	Privacy Risk → Continuance Intention to Use	−0.015	0.000	0.271 ns	0.009	0.000	0.169 ns	Not Supported
H8	Continuance Intention to Use → Word-of-Mouth Intention	0.579	0.774	10.671***	0.714	1.037	16.914***	Supported
H9	Continuance Intention to Use → Actual Use	-	-	-	0.593	0.544	13.324***	Supported
Control Relationships	Gender → Continuance Intention to Use	0.079	0.013	1.472 ns	0.016	0.001	0.436 ns	Not Significant
	Gender → Word-of-Mouth Intention	0.064	0.006	0.975 ns	0.016	0.000	0.359 ns	Not Significant
	Gender → Actual Use	-	-	-	−0.048	0.003	0.916 ns	Not Significant
	Age → Continuance Intention to Use	0.031	0.002	0.651 ns	−0.003	0.000	0.083 ns	Not Significant
	Age →Word-of-Mouth Intention	−0.064	0.006	1.112 ns	0.053	0.005	1.111 ns	Not Significant
	Age → Actual Use	-			0.004	0.000	0.051 ns	Not Significant
	Educational level → Continuance Intention to Use	0.033	0.002	0.541 ns	0.053	0.005	1.196 ns	Not Significant
	Educational level → Word-of-Mouth Intention	0.010	0.000	0.152 ns	0.012	0.000	0.176 ns	Not Significant
	Educational level →Actual Use	-	-		−0.055	0.003	0.836 ns	Not Significant
		R^2	Q^2		R^2	Q^2		
	Continuance Intention to Use	0.687	0.497		0.662	0.630		
	WOM Intention	0.436	0.306		0.509	0.535		
	Actual Behavior	-	-		0.352	0.273		

Note: n = 5000 subsamples; 95% confidence level—two-tailed. ns. not significant.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

young people aged between 18 and 24 years (40.16%), followed by individuals between 25 and 34 (19.69%); 60.56% were women. All the participants had used VAs for activities similar to those reported in Study 1. The participants used, as a preference, Apple's Siri (40.4%), Amazon's Alexa (37.4%), and Google Assistant (17.8%). The variables in Study 2 common to those in Study 1 were measured in the same way. In Study 2, personal innovativeness was measured using a scale adapted from Zhu et al. (2013), actual use by a scale adopted from Hernández-Ortega and Ferreira (2021), and level of experience by a scale adopted from McLean and Osei-Frimpong (2019) (Table 1).

4.2 | Measurement model assessment: Reliability and validity

The CA and CR scores exceeded 0.60 (Table 1), confirming the reliability of the scales (Hair et al., 2019). The AVE scores were also above the threshold, confirming convergent validity (Table 1). To evaluate discriminant validity, as in Study 1, the Fornell and Larcker (1981) criterion and the HTMT ratio (Henseler, Ringle, et al., 2016) were applied (Table 2). It is noteworthy that, as can be seen in Table 2, some inter-construct correlations were slightly higher than the square roots of the AVE values. Specifically, the square root of the AVE for quality value (0.781) is less than its correlation with price value (0.796), WOM intention (0.787), and emotional value (0.834); similarly, the square root of the AVE for performance expectancy (0.799) is less than its correlation with continuance intention to use (0.815). Nonetheless, the HTMT ratio offers acceptable values, and this criterion is a more stringent measure for assessing discriminant validity among latent variables, due to its robust performance, especially when used with the PLSc algorithm (Ringle et al., 2023; Roemer et al., 2021). Consequently, it is reasonable to say that our results confirmed the reliability and validity of the measurement model (see Table 2).

4.3 | Structural model assessment and hypotheses testing

The results provided support for several of the hypotheses. Perceived emotional value was found to have a significant positive influence on continuance intention to use VAs ($\beta3 = 0.482$, $t = 5.723$, $p < 0.001$), supporting H3. Perceived performance expectancy positively influenced continuance intention to use ($\beta6 = 0.349$, $t = 4.979$, $p < 0.001$), supporting H6. Continuance intention to use was found to positively influence positive WOM intention ($\beta8 = 0.714$, $t = 16.914$, $p < 0.001$), supporting H8. In addition, actual use of VAs was positively determined by continuance intention to use VAs ($\beta9 = 0.593$, $t = 13.324$, $p < 0.001$), providing support for H9.

In contrast, the hypotheses examining the influence of perceived quality value ($\beta1 = 0.080$, $p > 0.1$) (H1), perceived price value ($\beta2 = 0.026$, $p > 0.1$ (H2), perceived social value ($\beta4 = 0.069$, $p > 0.1$) (H4), perceived effort expectancy ($\beta5 = 0.031$, $p > 0.1$) (H5), and perceived privacy risk ($\beta7 = 0.009$, $p > 0.19$) (H7) on continuance intention to use VAs did not yield statistically significant results (Table 3).

To evaluate the capability of the structural model to make accurate predictions, Q^2 values were calculated through a blindfolding procedure/Stone-Geisser test. The Q^2 values obtained were 0.630 for continuance intention to use, 0.535 for intention to transmit positive WOM, and 0.273 for actual use, respectively. The R^2 values obtained indicated that the model explains 66.2% of the variance of continuance intention to use VAs, 50.9% of intention to transmit positive WOM and 35.2% of actual use. As in Study 1, the results were controlled for gender, age, and educational level, with no significant effects being observed (see Table 3).

To test the moderating effects of the two moderator variables (P1 and P2), two multigroup analyses, using the PLS-MGA technique, were performed (Sarstedt et al., 2011). Both variables were categorized into two values that were then used as criteria to divide the sample into groups. For the personal innovativeness variable, the mean value was used to create the two groups, that is, low and high personal innovativeness. Similarly, the sample was divided into two groups based on the level of experience declared by the participants, that is, inexperienced and experienced users (Figure 2).

Table 4 presents the results of the multigroup analysis. It can be concluded that the variables emotional value and performance expectancy have an important role as antecedents of continuance intention to use in the four groups generated to analyze the two moderating variables (low vs. high innovativeness; inexperienced vs. experienced users), although the effect of emotional value is particularly high in the experienced group. In addition, significant differences were observed between the paths of the two pairs of groups (low vs. high innovativeness; inexperienced vs. experienced users) due to the impact of the moderating variables. In particular, quality value influenced the continuance intention to use of those in the low innovativeness group, while its effect was not significant for those in the high innovativeness group, which supports $P1_1$. Similarly, the effect of social value is significant for experienced users, but not for inexperienced users, which supports $P2_4$.

4.4 | Discussion of Study 2

The results of Study 2 are consistent with those obtained in Study 1. Both studies confirmed that the value perceived by users and, to a lesser extent, performance expectancy, are important predictors of continuance intention to use VAs, which in turn is a key antecedent of intention to transmit positive WOM. In addition, the results of Study 2, similarly, did not show that price value, social value, effort expectancy, or privacy risk were significant. However, one difference between the results is that in Study 2 quality value did not exert a significant influence, but it did in Study 1.

On the other hand, as to the new effects incorporated into Study 2, it should be noted that the results confirmed the capacity of continuance intention to use to predict actual use. Also, although only partially, the effects of the two moderating variables were confirmed as less innovative users were shown to be sensitive to quality value, and experienced users were sensitive to social value.

5 | CONCLUSIONS

5.1 | Theoretical implications

Many studies have analyzed the processes of adoption and use of AI-powered agents, using a wide diversity of theoretical frameworks (Camilleri & Troise, 2023; Mariani et al., 2022). Nonetheless, some authors (e.g., Belk et al., 2020) have argued that more work needs to be carried out into the combined effects of the reasons for and against intention to use the devices. Similarly, the literature highlights the need to increase the understanding of the value generation process in the context of these technologies (e.g., Flavián & Casaló, 2021) and of the moderating effect of users' personal characteristics (Belanche et al., 2020; Camilleri & Troise, 2023). In addition, as Westaby (2005) suggests, the factors for and against the use of technologies are determined by the type of technology. To date, while some studies have analyzed the factors that influence the acceptance of AI-powered agents, very few have used BRT (Camilleri & Troise, 2023; Ling et al., 2021; Mariani et al., 2022). Thus, the present study has increased the understanding of the factors that influence users' continuance intention to use VAs and the ability to predict both users' intentions to transmit positive WOM about VAs and users' actual use of VAs, taking into account the moderator effects of personal innovativeness and experience. To achieve this, a conceptual model based on BRT was proposed and evaluated in two studies that used data collected through online surveys involving two independent samples. The study makes several contributions to the literature on the adoption and use of VAs.

First, the results of both studies showed that emotional value was the main generator of users' continuance intention to use VAs. This result extends the contribution of previous studies that demonstrated that perceived value had a positive effect on user-VA relationship quality (e.g., Loureiro et al., 2021), by identifying which of the dimensions of perceived value is decisive for the

TABLE 4 Tests of moderation effects (personal innovativeness and experience).

Propositions	Paths	High Innovativeness	Low Innovativeness	Comparison	Significant difference
$P1_1$	Quality Value → Continuance Intention to Use	−0.049 ns	0.288* (p = 0.044)	2.630	Yes
$P1_2$	Price Value → Continuance Intention to Use	−0.021 ns	−0.088 ns	0.436	-
$P1_3$	Emotional Value → Continuance Intention to Use	0.554***	0.357***	1.048	-
$P1_4$	Social Value → Continuance Intention to Use	−0.052 ns	−0.114 ns	0.641	-
$P1_5$	Effort Expectancy → Continuance Intention to Use	0.056 ns	−0.024 ns	0.566	-
$P1_6$	Performance Expectancy → Continuance Intention to Use	0.375***	0.371***	0.032	-
$P1_7$	Perceived Privacy Risk → Continuance Intention to Use	−0.023 ns	0.033 ns	0.533	-
$P1_8$	Continuance Intention to Use → Word-of-Mouth Intention	0.712***	0.622***	0.866	-
$P1_9$	Continuance Intention to Use → Actual Use	0.605***	0.558***	0.453	-
Propositions	**Paths**	**Experienced**	**Inexperienced**	**Comparison**	**Significant difference**
$P2_1$	Quality Value → Continuance Intention to Use	0.023 ns	0.142 ns	0.688	-
$P2_2$	Price Value → Continuance Intention to Use	−0.099 ns	0.003 ns	0.697	-
$P2_3$	Emotional Value → Continuance Intention to Use	0.625***	0.397***	1.197	-
$P2_4$	Social Value → Continuance Intention to Use	−0.192**	−0.027 ns	1.757	Yes
$P2_5$	Effort Expectancy → Continuance Intention to Use	−0.019 ns	0.034 ns	0.375	-
$P2_6$	Performance Expectancy → Continuance Intention to Use	0.334***	0.358***	0.158	-
$P2_7$	Perceived Privacy Risk → Continuance Intention to Use	0.056 ns	−0.008 ns	0.551	-
$P2_8$	Continuance Intention to Use → Word-of-Mouth Intention	0.694***	0.714***	0.222	-
$P2_9$	Continuance Intention to Use → Actual Use	0.607***	0.541***	0.734	-

Notes: comparison means the t value of coefficient difference comparison; ns, not significant.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

creation of continuance use intention. Users' interactions with VAs generate in their feelings of enjoyment, pleasure, and well-being that encourage them to continue using the devices. In addition, as Hernández-Ortega and Ferreira (2021) noted, consumers come to communicate emotionally with their VAs, that is, as if they were people, and develop feelings toward them; the emotional dimension, thus, is key in maintaining these relationships.

Second, although to a lesser extent than emotional value, performance expectancy is also an important antecedent of continuance intention to use. That is, the utilitarian and functional benefits that users perceive they derive from using VAs to perform their daily tasks is a very important reason they continue using them. This result is consistent with the results of previous research into technology adoption (Venkatesh et al., 2012), in particular, with those of recent studies into conversational agents (Ling et al., 2021) and VAs (Ashfaq et al., 2020; Vimalkumar et al., 2021). This finding expands the contribution of previous studies by demonstrating the effects of performance expectancy, not on intention to use, but on continuance intention to use. In addition, it expands on the contributions of Jain et al. (2022) and Maroufkhani et al. (2022), who showed that performance expectancy affected continuance intention to use through overall perceived value; in the present study, it has been shown that the effect can be direct.

Third, this research showed that quality value is not a consistent driver of continuance intention to use VAs; its effect was significant only in Study 1 and in one of the groups set up to demonstrate the moderator effects of personal innovativeness. To date, studies into technology use have often regarded quality value as an antecedent of other variables, such as perceived ease of use and trust. The present study has shown that quality value may have a direct effect on continuance intention to use VAs, and calls for further research to be undertaken to obtain a better understanding of this relationship.

Fourth, the results of both studies showed that price value, social value, effort expectancy, and perceived privacy risk have no significant effects on continuance intention to use. As discussed above, price value may have no effect on continuance intention to use because many users employ VAs incorporated into multi-functional devices (e.g., computers, smartwatches, and cars); thus, it is difficult to undertake an effective cost–benefit analysis of using the devices. Since Venkatesh et al. (2012) proposed that price value is an antecedent of intention to use technologies, many studies have confirmed the relationship. The present study contributes to the literature by showing that the influence of price value on continuance intention to use may not be significant, even at the relatively low prices charged for some VAs, if users cannot easily discern how much they cost, particularly in comparison to other consumer technologies with clearly established prices (e.g., paid-for apps).

Social value relates to the utility consumers expect to derive from the capacity of their VAs to improve their self-concepts. Contrary to the prediction, in the present study, VAs' social value did not exert a significant effect on continuance intention to use the devices. Kulviwat et al. (2009) observed that the effects of social influence on intention to use a high-technology innovation are stronger when the innovation is used publicly, rather than privately. This result may have occurred because the most frequent current use context of VAs is private (e.g., at home, in one's car), so it is possible that the user's social environment (friends and acquaintances) will be unaware of the use that (s)he makes of his/her VA. This finding expands on the contributions of Ashfaq et al. (2020), who also found that social value did not improve users' attitudes toward VAs.

The effort expectancy, or degree of ease, associated with VA use was not shown to significantly influence continuance intention to use. Traditionally, the literature on the adoption and use of technologies has shown that consumers' likelihood of adopting technologies is proportionate to their user-friendliness (Venkatesh et al., 2003; Venkatesh et al., 2012). This relationship has also been demonstrated in the conversational agent literature (Lim et al., 2022). However, the finding of the present study, consistent with the results of recent work undertaken by Fernandes and Oliveira (2021), is that ease of use is not a determining factor for continuance intention to use VAs. This result may be due to the fact that users' interactions with VAs are based on natural-language processing; thus, they find the devices readily accessible and very simple to use; this feature perhaps leads users to evaluate VAs based more on their emotional and functional benefits. In addition, as suggested by Davis (1989), it may be that effort expectancy has an indirect influence, through performance expectancy, on continuance intention to use; future works might explore these relationships to increase the knowledge of the effects of effort expectancy in the VA context.

Similarly, perceived privacy risk was not found to have a significant effect on continuance intention to use VAs. This result, which is similar to that recently obtained by Vimalkumar et al. (2021), is surprising, particularly given that it is known that many consumers are aware of those VA characteristics that enable them to compromise personal data/information, and to make inappropriate use of the data/information. The literature has frequently shown that perceived risk decreases intention to use technologies; nonetheless, this effect is mainly observed with technologies that can carry financial risk, such as e-commerce (Li & Choudhury, 2021). However, the present study examines privacy risk, and it is perhaps more difficult to assess this in the context of VAs, which are used mainly to perform low-engagement tasks (e.g., listening to music vs. buying a product). Therefore, it is possible that the absence of any effect of perceived privacy risk is explained in this context due to what has been called the privacy paradox, that is, consumers are willing to run risks when they believe that the benefits they obtain thereby are greater than the potential costs they might face (Vimalkumar et al., 2021). In this sense, the findings of the present study reinforce the applicability of the privacy paradox to the VA context.

Fifth, continuance intention to use VAs was shown to significantly influence both intention to transmit positive WOM and actual use. These results are in line with the literature, although few studies have, to date, demonstrated these relationships in the VA context. Maroufkhani et al. (2022) showed that continuance intention to use influences brand loyalty toward VAs; Vimalkumar et al. (2021) demonstrated that continuance intention to use had a significant effect on VA adoption; and Mishra et al. (2022) showed that users' hedonic and utilitarian attitudes affected actual use and WOM. Therefore, the present study contributes to the literature by demonstrating, in the same work, consistently over two studies, that continuance intention to use predicts intention to transmit positive WOM, and actual use.

Finally, this study also examined the moderating effects of two psychographic characteristics, personal innovativeness, and experience, in the relationships between the model's antecedent variables and the consumer's continuance intention to use VAs, and in the relationships between continuance intention to use and his/her intention to transmit positive WOM, and his/her actual use. The results showed that quality value exerts a significant effect on continuance intention to use among users with low personal innovativeness. This may be because low innovative users may be less demanding about features such as the quality of service provided by VAs, their design, their functionality, and their durability than are high personal innovativeness users. It should be remembered that the effect of this variable was significant in Study 1, but not in Study 2, thus examining moderation allows us to better understand the role of service quality. These findings are an important contribution because this relationship has been very little explored in the literature, and because they offer a different perspective of the consequences of personal innovativeness, given that there is a widespread belief that this characteristic encourages users to evaluate new technologies positively (Agarwal & Prasad, 1998), particularly in regard to service quality (Dai et al., 2015).

Regarding the moderating effects of experience, the results showed that social value significantly decreases continuance intention to use VAs among users with more experience of the devices.

This result takes an opposite direction to what one might expect, given that it implies that the greater the user's perceptions of the social value (s)he might derive, the lower will be his/her continuance intention to use. Risselada et al. (2014) demonstrated that the effects of social influence on the adoption/use of high-technology products are not constant, but dynamic, that is, they tend to diminish as the presence of the products in the market increases. The present study extends this dynamic effect concept by showing that, for a given profile of users (experienced), a negative relationship exists between social value and continuance intention to use VAs. This outcome may occur because experienced users pay more attention to their own evaluations of VAs than they pay to social influence (Alba & Hutchinson, 1987). In addition, the extension of VAs into wider society may have reduced their attractiveness for more experienced users, who regard technology use an indication of social status (Eckhardt & Bardhi, 2020), so users with less social status might be more sensitive to social influence (Kaba, 2018). Further research, therefore, is needed to check the validity of the model's results.

5.2 | Practical implications

The results of this research raise important practical considerations. Specifically, it should be borne in mind that the user, while (s)he knows (s)he is talking to an AI-powered agent, interacts emotionally as if it were another person. Therefore, VA developers might enhance the ability of their devices to connect emotionally with users during their interactions. This will allow the devices to analyze not only the language, but also the tone, employed by users, which will help them better understand the user's mood, promote empathy and adapt to the user's emotional state. This capability would open up opportunities for VAs to become more than just functional tools, that is, to be the consumers' life partners (Hernández-Ortega & Ferreira, 2021); thus, they must be able to develop relationships similar to those established between humans, to anticipate the needs of the users and to understand their preferences. To promote the creation of emotional relationships, VA developers might enhance the ability of the devices to interpret and express emotions through the valence of words and tone of voice and apply elements that might humanize the devices (e.g., name, age, gender, voice, and image).

Similarly, the devices must help users to perform the actions they want to undertake quickly and efficiently, because their continued use will be strongly determined by their ability to complete the tasks set by their users. It must not be forgotten that, after emotional value, performance expectancy (or functional/utilitarian benefits) was the second most influential antecedent of continuance intention to use VAs. For example, developers might optimize VAs' responses and personalization by configuring them to proactively learn the needs and interests of their users from various information sources (e.g., social networks, websites, previously used services, shopping lists).

In addition, developers and manufacturers should also pay attention to quality value (design, materials, reliability, etc.) as its influence can be decisive for continuance intention to use, particularly among users with low personal innovativeness. For example, when searching the internet for information to respond to users' requests, VAs often do not have the ability to assess the reliability of sources, which leads them to provide untrustworthy or inaccurate information. Developers could improve the search engines that VAs access and establish indicators that will allow their users to assess the reliability of information sources.

It seems that VA manufacturers need not lower their prices or promote the social image capabilities of the devices, as these factors were not found to have a significant effect on continuance intention to use, although this does not mean that the effect does not exist. Similarly, users seem to use VAs with such ease due to their natural language processing function, to the extent that they already consider that using them is so normal that ease of use does not have a significant effect on continuance intention to use, although the effect might exist with some users. It could be said that, in addition, while consumers retain privacy concerns, VA suppliers (e.g., Apple, Amazon, and Google) need not focus too much on the security of/and trust in, their systems in their communications, because perceived privacy risk does not seem to have a significant effect on consumers' decisions to use the devices. However, it is possible that perceived risk will come to play a more important role in use decisions as VAs are employed more for tasks involving financial data (e.g., online shopping). Therefore, developers might improve their privacy policies, for example, by not storing all the information that VAs pick up when they are turned on, and by not using any information collected for commercial purposes.

Finally, companies must take into account users' psychographic characteristics because, as has been demonstrated, personal innovativeness and experience can influence, to a greater or lesser extent, some of the antecedent variables of continuance intention to use. In this sense, the results suggest that quality value should be emphasized in communications aimed at users with low personal innovativeness. In addition, more experienced users should be targeted with VA versions possessing new functionalities that might maintain their interest in the devices. By tailoring their communications and design strategies to users' characteristics, companies can increase the use and recommendation of VAs.

5.3 | Limitations and future research

Despite its contribution, this research has some limitations. First, although the research is based on two cross-sectional studies using data collected in two consecutive years, future research might analyze the stability of the relationships over time in a longitudinal study. Second, the data were collected in Spain, thus, it would be advisable, to increase the generalizability of the results, to reproduce the study in other cultural environments. Third, although the characteristics of the samples of the two studies are quite similar, there are small differences between them that we suggest means the results should be interpreted with caution, as they may be affected by unobserved factors. Fourth, although the study evaluated the moderating effects of two psychographic characteristics of VA users, other potential moderators of the VA-consumer relationship require further exploration in the future (e.g., perceived psychological power, perceived intrusiveness, perceived VA anthropomorphism). Fifth, it would be interesting to examine differences among high, medium, and low levels of innovativeness and experience with VAs. This three-group segmentation might provide additional insights into the nuances of how these factors might moderate the model's relationships. Sixth, although the personal innovativeness variable facilitates the analysis of how the way that users handle technological innovations affects their behaviors, an additional perspective might be provided if future studies differentiated between early and late adopters, within the framework of diffusion of innovation theory. Seventh, recent studies have shown that product type (e.g., search vs. experience, low vs. high involvement) moderates consumers' perceptions and behaviors in their interactions with VAs (Flavián et al., 2023), so future work might explore the effects of other features, such as product innovation and price. Finally, users employ VAs to perform a wide variety of tasks; thus, future works might evaluate whether continuance intention to use is affected by the type of task performed.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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