The influence of brand credibility and brand loyalty on customer satisfaction and continued use intention in new Voice Assistance Services based on AI

Abstract:

The use of Voice Assistance Systems based on Artificial Intelligence (VASAI) - such as Siri, Alexa, and many others- is becoming more and more popular; however, studies on this topic are still scarce. One of the topics that has only been tangentially addressed is the impact of brand-related issues (such as brand credibility and brand loyalty) on customer satisfaction and continued use intention of VASAI. The present study addresses this topic by postulating a structural model for its evaluation. The author's structural model also examines the influence of system quality constructs (system stability, system agility, and anthropomorphism), and information quality constructs (information exhaustiveness or information up-to-datedness) as independent variables. The researcher uses a questionnaire, based on previous literature, which is administered to a sample of 651 participants. The proposed structural model is evaluated by applying PLS-SEM analysis. The results show that brand credibility influences the constructs of customer satisfaction (β=0.289 / p-value <.001) and continued use intention (β=0.304 / p-value <.001). Similarly, the findings indicate that brand loyalty has a moderating effect on the relationships between brand credibility and consumer satisfaction, on the one hand, and brand credibility and continued use intention, on the other. In view of the results, the author concludes that some brand-related constructs have an impact on customer satisfaction and intention to continue using VASAI, indicating the critical importance of brand management for the success and future development of these technologies.

Keywords: brand credibility; brand loyalty; customer satisfaction; use intention; AI; Alexa; moderating effect.

1. Introduction

Terms such as "intelligent voice assistant" or "personal intelligent assistant" are often used interchangeably with other terms such as "digital assistant", "interactive assistant", "voice assistant", "artificial intelligence agent", or even "chatbot" (Song et al., 2022). However, probably the most appropriate name for this type of technology is "Voice Assistance System based on Artificial Intelligence" (hereafter VASAI). Examples of these technologies include Siri (Apple), Xiao AI (Xiaomi), Alexa (Amazon), Cortana (Microsoft), Bixby (Samsung), and other lesser-known agents used by many companies on their websites. VASAI have changed the way users perform basic personal tasks and search for information, but also the way companies and brands interact with consumers (McLean et al., 2021).

Studies examining the adoption drivers of these technologies focus primarily on the user's personal traits and attitudes; while those aimed at exploring post-adoption behaviors usually consider behavioral, psychological, and marketing aspects (Lim, Kumar, Pandey, Verma, and Kumar, 2023). One of the models used for analyzing the factors influencing VASAI adoption is the Expectation Confirmation Model (ECM) (Ghazali et al., 2023; Huang and Yu, 2023). This model examines how the system is able to meet the user's prior expectations, but also explores what factors may contribute to its continued use. Similarly, several authors have also used Parasocial Theory (PT) (Lee and Park, 2022; Youn and Jin, 2021). This theory focuses on examining how interactions with VASAI influence consumers' perceptions of quality, satisfaction, and ultimately, intentions for continued use.

Previous research, both in ECM and PT, has built a solid knowledge base about the adoption drivers in VASAI and the post-adoption behaviors when using these systems; nevertheless, the research has also left out aspects of great importance. One of the issues that has only been tangentially addressed is the study of the role of VASAI as a value-added element for the consumer within the company's marketing and branding strategy. That is, how VASAI can add value to the company's brand, but also how the company's brand influences the customer's perception of VASAI (Ghazali et al., 2023; Jain et al., 2022; Maroufkhani et al., 2022).

According to previous research (Ghazali et al., 2023; Jain et al., 2022; Maroufkhani et al., 2022), the literature has not paid enough attention to how the company's brand influences the user's disposition towards VASAI. Conversely, it is known that only continuous use and feedback from the user allows VASAI to learn, and with it the development and consolidation of the system, as happens with any other AI-based technology. Therefore, it seems necessary to evaluate the extent to which brand-related issues affect consumers' behavior after using VASAI, both in terms of their satisfaction and their intention to use it.

By expanding the theoretical frameworks of ECM and TP, the current study seeks to fill this gap in the literature by analyzing the impact of brand credibility and brand loyalty on customer satisfaction and intention to continue using these technologies. Therefore, this research is in line with Petrescu and Krishen's (2023) call to explore the role of AI in marketing and brand strategies, or Schiessl, Dias, and Korelo's (2022) call to investigate the brand role in the context of AI. But most importantly, the present research responds to the call of Lim et al. (2023) to explore consumer commitment with AI-based technologies, such as VASAI, not only from a technical perspective, but also from a marketing approach.

The manuscript begins by presenting the background and prior theoretical framework, the rationale for the proposed structural model, and the hypotheses (Section 2). This is followed by a description of the methodology used, describing the sampling procedure, the operationalization of constructs, and the analytical techniques employed (Section 3). The paper concludes with a discussion and conclusion, indicating the limitations of the study and future directions for research.

2. Theoretical framework and hypothesis development

Among the most widely used theoretical models to study technology adoption, in general, and VASAI, in particular, are the Technology Acceptance Model (TAM) (De Cicco et al., 2022) or the Unified Theory of Acceptance and Use of Technology (UTAUT) (Balakrishnan et al., 2022). Nonetheless, these two models primarily focus on the drivers of technology adoption and do not sufficiently address post-adoption behaviors such as customer satisfaction or prospect of continued use.

TAM assesses the propensity of users to adopt new technologies. This model suggests that when users adopt a technology, three factors influence their decision: 1) the subject's perception of how the use of the technology will be helpful; 2) the perceived ease of use; and 3) the enjoyment the subject derives from using the technology (Ho et al., 2021). Similarly, UTAUT seeks to explain users' intentions to use technology and their behavior after subsequent use. This theory suggests that there are four important factors to take into account: 1) Expected benefits; 2) Expected effort; 3) Social influence of the environment; and 4) Facilitating environmental conditions. The first three would be determinants of usage intention, while the fourth would be a determinant of usage behavior (Venkatesh et al., 2003). Nonetheless, the focus of these two models, and where they provide greater explanatory power, is more on the adoption drivers than on post-adoption issues such as customer satisfaction or future use perspectives (Martinez and McAndrews, 2022).

However, it must be emphasized that VASAI's efficiency depends directly on its ability to continuously learn from user feedback. Consumer feedback indicates whether the information provided by the system is correct or not. This allows VASAI to check the level of correctness of the response, learn from it, and provide better responses in the future. Therefore, both customer satisfaction and intention to continue using the system are critical to the development and evolution of these technologies. In other words, the efficiency and success of the system depends on how the assistant responds to requests, on the user's feedback, and on whether the customer's expectations are met.

Recently, several researchers (Ghazali et al., 2023; Huang and Yu, 2023) have also introduced the ECM or PT as a theoretical framework to study VASAI and assess how the technology meets customer expectations and how these expectations evolve over time. The first one, -ECM- has been used primarily to explore the factors that influence the adoption of VASAI, but also to examine which variables may contribute to individual satisfaction and continued use (Ghazali et al., 2023; Huang and Yu, 2023). The second, -

PT- has been mainly used to analyze the post-adoption behavior of users over time (Ghazali et al., 2023; Lee and Park, 2022).

Beyond the above theoretical frameworks, the non-systematic literature review conducted by the author confirms that recent research on this topic can be divided into two main groups. On the one hand, studies on the analysis of the adoption drivers of VASAI and, on the other hand, research on the post-adoption situations (see Table 1). Regarding studies focusing on adoption drivers, three main subcategories can be distinguished. First, research on the utilitarian features of VASAI; studies that explore issues such as perceived usefulness, attitudes toward technology, or perceived risks and privacy concerns (Acikgoz and Vega, 2022; Fernandes and Oliveira, 2021; Schreibelmayr and Mara, 2022). Second, the research focused on the hedonic features, such as the perception of enjoyment or the playfulness and entertainment that the user finds in the system (Ischen et al., 2020; Malodia et al., 2021; Rzepka et al., 2022). And third, research on the social presence perceived by the user, such as the contextual conditions in the environment or the anthropomorphism of the VASAI as a way to create a sense of social presence in front of the consumer (Crolic et al., 2022; Han, 2021; Ramadan, 2021).

Table 1. Relevant studies on the use of VASAI (First part)

Main category	Subcategory	Topics analyzed	Relevant studies	Findings / Conclusions / Implications
Studies on adoption drivers	Studies on utilitarian features	Perceived usefulness	(Acikgoz and Vega, 2022; Fernandes and Oliveira, 2021; Malodia et al., 2021; McLean and Osei-Frimpong, 2017)	Most studies include perceived usefulness as an independent variable in the analysis. In the same way, most of the studies suggest that perceived usefulness has a positive impact on the adoption drivers of VASAI.
		Attitude towards technology	(De Cicco et al., 2022; Schreibelmayr and Mara, 2022; Sohn and Kwon, 2020)	Most of the studies consider the attitude towards technology as an independent variable in the analysis. Likewise, most studies suggest that attitude toward technology has an impact on the adoption drivers of VASAI.
		Perceived risks and privacy concerns	(Acikgoz and Vega, 2022; Hasan et al., 2021; Jain et al., 2022; Rese et al., 2020; Thomaz et al., 2020; Wach et al., 2023)	Most studies analyze perceived risks and privacy concerns as independent variables. In the same way, most studies suggest that perceived risk and privacy concerns have a negative impact on the adoption of VASAI.
	Studies on hedonic features	Perception of enjoyment	(Ischen et al., 2020; Jain et al., 2022; Melián-González et al., 2021; Rzepka et al., 2022)	Most studies use the perception of enjoyment as an independent variable in the analysis. Many studies suggest that perception of enjoyment has a positive influence on the acceptance factors of VASAI. Other studies indicate that there is no effect.
		Playfulness and entertainment	(De Cicco et al., 2022; Malodia et al., 2021; Mishra et al., 2022; Söderlund and Oikarinen, 2021)	Most studies consider playfulness and entertainment as independent variables in the analysis. The studies suggest that hedonic value mediates the effects of playfulness and entertainment on the adoption drivers of VASAI.
	Studies on social presence	Context and environment	(Pillai and Sivathanu, 2020; Ramadan, 2021; Wirtz et al., 2018)	Depending on the study, context and environment can be considered as independent or dependent variables. The use of VASAI has been analyzed in different macro-environments, industries, and settings.
		Anthropomorphism	(Balakrishnan et al., 2022; Crolic et al., 2022; Han, 2021; Moriuchi, 2021; Mousavi et al., 2020; Seo, 2022)	Most studies treat anthropomorphism as an independent variable in the analysis. The results suggest that the effect of anthropomorphism can be positive or negative depending on the availability and perceived usefulness of the information provided.

Source: Own elaboration

Table 1. Relevant studies on the use of VASAI (Continued)

Main category	Subcategory	Topics analyzed	Relevant studies	Findings / Conclusions / Implications
Studies on post-adoption behavior of users	Studies with a user / consumer approach	Continued usage	(Ghazali et al., 2023; Huang and Yu, 2023; Jain et al., 2022; Molinillo et al., 2023)	Most studies consider continued usage as a dependent variable in the analysis. Studies suggest that a variety of factors may influence continued usage of VASAI.
		Compliance with system recommendations	(Adam et al., 2021; Hildebrand and Bergner, 2021; Zarouali et al., 2021)	Most studies analyze compliance with system recommendations as a dependent variable. Studies suggest that affective trust may have an impact on compliance with VASAI recommendations.
		Purchase intention	(Crolic et al., 2022; Khoa, 2021; McLean et al., 2021; Shah et al., 2023; Sohn and Kwon, 2020)	Most studies use purchase intention as a dependent variable in the analysis. Research suggests that factors related to the use of VASAI do not always have a positive impact on purchase intention.
		Customer satisfaction with the system	(Crolic et al., 2022; Jiménez-Barreto et al., 2023; Mishra et al., 2022; Sands et al., 2021)	The results vary depending on the study and the independent variables used in the analysis. However, it is observed that the utilitarian and social factors of VASAI have an impact on customer satisfaction with the system.
	Studies with a corporate approach	Branding	(Ghazali et al., 2023; Jain et al., 2022; Maroufkhani et al., 2022; McLean et al., 2021)	The studies suggest that branding, generally analyzed as an independent or moderating variable, may or may not have an impact on post-adoption behavior, depending on the branding approach and branding constructs considered in the analysis.
		WOM and eWOM	(Chu et al., 2019; Hernandez-Ortega and Ferreira, 2021; Mishra et al., 2022; Molinillo et al., 2023)	Most studies consider WOM and eWOM as dependent variables in the analysis. Findings suggest that under certain circumstances, satisfaction may influence WOM and eWOM.
		Loyalty	(Hernandez-Ortega and Ferreira, 2021; Jenneboer et al., 2022; Maroufkhani et al., 2022; Moriuchi, 2021)	Depending on the study, loyalty can be considered as independent or dependent variable. The results show both relationships of influence and situations of lack of influence, depending on the variables included in the analysis.
		Customer satisfaction with the company or product	(Chung et al., 2020; Pizzi et al., 2021; Poushneh, 2021)	The results vary depending on the study and the independent variables used in the analysis. However, it is observed that the hedonic and social factors of VASAI have an impact on customer satisfaction with the company or product.

Source: Own elaboration

As far as research on post-adoption situations is concerned, two main categories of studies can be observed. On the one hand, research that takes a user or consumer approach; such as the studies addressing issues like continued usage, compliance with system recommendations, purchase intention, or customer satisfaction with the VASAI (Adam et al., 2021; Khoa, 2021; Molinillo et al., 2023; Shah et al., 2023). On the other hand, there are studies that take a corporate approach; the case of studies that address issues such as branding, WOM and eWOM, loyalty or customer satisfaction with the company or product (Ghazali et al., 2023; Hernandez-Ortega and Ferreira, 2021; Mishra et al., 2022; Pizzi et al., 2021). Table 1 summarizes some of the studies that, in the author's opinion, have gain more relevance on the analysis of the topics previously mentioned.

The present study is based on the findings of the PT, examining satisfaction and intention for continued use of VASAI from a slightly different perspective; but it is also based on the ECM. According to the ECM, the confirmation of expectations, before the adoption of the technology, influences the cognitive evaluation of its usefulness, but also the user's satisfaction after the adoption (Mamun et al., 2020; Oghuma et al., 2016). In addition, the ECM also addresses the fact that after initial adoption, user satisfaction may change. These changes cause the user to abandon or repeat the behavior, which ultimately determines the intention for continued use.

The original ECM postulates that there are four dimensions to be assessed: 1) Expectancy fulfillment; 2) Perceived usefulness; 3) Satisfaction after use; and 4) Intention for continued use (Bhattacherjee, 2001). The present research, in line with the studies of Ghazali et al. (2023), Jain et al. (2022), and Maroufkhani et al. (2022), takes the dimensions of satisfaction after use and intention for continued use to give shape to the second part of the proposed model. In addition, the author incorporates brand-related constructs -such as brand credibility and brand loyalty- that may be determinant in the use context of VASAI. The model also examines the influence of system quality constructs -such as the performance stability, the response agility, and the anthropomorphism- and information quality constructs -such as information exhaustiveness or information up-to-datedness- as independent variables. The justification for the appropriateness of the above constructs, in addition to the formulation of the hypothesis, is discussed below.

2.1. Hypothesis posed

The first part of the structural model examines the influence of the aspects related to system quality (system stability, system agility, and anthropomorphism) and information quality (information exhaustiveness, and information up-to-datedness) in brand credibility.

In accordance with Erdem and Swait (1998), brand credibility is the ability of a brand to consistently deliver on its promises. Similarly, Dwivedi et al. (2017) conceptualized brand credibility as the customer's relationship with a brand over time. For Baek et al. (2010), brand credibility is associated with higher perceived value and consumers' attitudes toward brand attributes. According to previous research, both in the general field of marketing (Erdem and Swait, 2004; Sweeney and Swait, 2008) and more recently, specifically, in context of AI-based technologies (Ghazali et al., 2023; Jain et al., 2022), brand credibility consists of two constructs, brand trustworthiness and brand expertise.

The present research, in line with Erdem and Swait (2004), Sweeney and Swait (2008), Ghazali et al. (2023), and Jain et al. (2022), adopts the construct of brand credibility as a result of these two sub-constructs (brand trustworthiness and brand expertise).

In the second part of the model, the researcher examines how the construct of brand credibility influences the constructs of customer satisfaction and continued use intention of VASAI. The final Appendix provides a description of all the constructs considered in the structural model.

2.1.1. System stability

The ability of the system to deliver quality service is one of the most important aspects when evaluating VASAI. Parasuraman (2000) points out that service quality is one of the key dimensions in the customer's evaluation of any technology. According to Saeed and Abdinnour-Helm (2008), the quality of a technological service is determined by the degree of stability with which the system effectively performs its functions. As a result, when VASAI presents unstable performance, the user experience is ineffective and subjects are forced to make extra effort to perform their tasks. On the contrary, when the system performs adequately and consistently, the user experience is enhanced, which in turn improves the consumer's attitude toward the brand. Hasan, Shams, and Rahman (2021) address that when VASAI provides stable performance, it positively affects the involvement and trust in the brand. Considering that, according to various authors (Ghazali et al., 2023; Jain et al., 2022), brand trustworthiness or brand expertise are constituent elements of brand credibility, the following hypothesis is posed:

H1. *System stability in its performance has a positive effect on brand credibility.*

2.1.2. System agility

System quality can be reflected in several attributes (system stability, as mentioned above, is one of them); and system agility in speech recognition and response time are also key variables in this regard. According to Nguyen et al. (2022), features such as accent recognition, and conversational context understanding have greatly improved user perception, and this ultimately also influences the subject's view of the system. If the VASAI is not able to recognize speech and provide quick responses, the consumer experience could be negatively affected. On the contrary, if the user perceives that the system is able to provide agile responses, the consumer is likely to associate this with good expertise, which may also promote trust in the company (Hasan et al., 2021). In addition, Ghazali et al. (2023) indicate that elements associated with system quality, as is the case with system agility, influence brand trustworthiness, as a sub-construct of brand credibility. In light of these circumstances, the author proposes the following hypothesis:

H2. *System agility in its responses has a positive effect on the brand credibility.*

2.1.3. Anthropomorphism

Anthropomorphism, or the degree of humanity perceived by the individual, is another key element. Anthropomorphism is shown in aspects such as natural language processing or the relative personification of the system. Previous studies show that it is essential for VASAI developers to increase the perceived humanity of the system in order to strengthen the connection between the user and the assistant (Habler et al., 2019; Schreibelmayr and Mara, 2022). Thus, it is common for brands to employ close appellations and human reminiscences for these technologies (case of Alexa or Siri). Similarly, brands endow VASAI with distinct personalities and provide them with the ability to joke. All of this contributes to creating a connection between the user, the technology, and ultimately the brand behind it, evoking feelings of warmth, social connection, and trust that lead consumers to improve their attitude toward the brand (Hanlon, 2022). Going further, Ghazali et al. (2023) indicate that anthropomorphism conditions both brand trustworthiness and brand expertise, as constituent elements of brand credibility. Therefore, the author postulates the following hypothesis:

H3. *Anthropomorphism of the system has a positive effect on the brand credibility.*

2.1.4. Information exhaustiveness

In any information system, the quality of the information is obviously a critical factor, not only to develop better service levels for the user, but also to improve the perception of the brand's attributes (Saeed and Abdinnour-Helm, 2008). In the case of VASAI, inaccurate or irrelevant information may cause the user to spend more time and effort than necessary and may cause the consumer to seek alternative solutions. On the contrary, when VASAI is able to provide complete and accurate information, it creates a positive attitude toward brand expertise, which can also have a positive impact on brand trustworthiness. In addition, Jain et al. (2022) suggest that higher brand credibility (based on brand trustworthiness and brand expertise) reduces users' privacy concerns. In the same line, Coulter and Coulter (2003), address that the system's ability to generate knowledge can even serve to mitigate risk perception in the use of technology, thereby improving the consumer's attitude toward the brand. Under these circumstances, the author proposes the following hypothesis:

H4. *Information exhaustiveness has a positive effect on brand credibility.*

2.1.5. Information up-to-datedness

Previous studies suggest that information quality and conversation, broadly defined, are critical measures in evaluating this type of service. In the case of VASAI, the quality of the information is determined by different variables (such as the information exhaustiveness previously indicated), and one of them is the timeliness of the answers provided. Previous research suggests that the system's ability to provide updated information and timely responses could have an impact on brand-related issues (Ashfaq et al., 2020; Chung et al., 2020). According to Ou and Sia (2010), when technology is able to provide answers with current and updated information, it improves consumer trust. In the same line, Ghazali et al. (2023) address that elements associated with information quality, which is the case of the information up-to-datedness, influence brand expertise as a sub-construct of brand credibility. Therefore, the author proposes the following hypothesis:

H5. *Information up-to-datedness has a positive effect on the brand credibility.*

2.1.6. Brand credibility

Brand credibility, according to previous research (Erdem and Swait, 1998; Jain et al., 2022), consists of two sub-constructs, brand trustworthiness and brand expertise. On the other hand, satisfaction is the customer's response when a product, service, or technological feature, offers a level equal to or higher than expected, after its use or consumption, and this is what leads the customer to maintain the relationship with the firm (Oliver, 2014). Sweeney and Swait (2008) point out that brand expertise can also affect customer satisfaction with the company's service or product. But furthermore, in the particular context of VASAI, Ghazali et al. (2023) suggest that brand trustworthiness and brand expertise, as constituent elements of brand credibility, condition customer satisfaction in the use of VASAI. In light of this situation, the author propose the following hypothesis:

H6. *Brand credibility has a positive effect on customer satisfaction.*

Yang, Ji, and Tan (2022) suggest that AI-based technologies can redesign the customer journey by providing personalized solutions that encourage consumers to continue their relationship with the company. In the same vein, Seeber et al. (2020) address that VASAI are often customer experience collaborators. Both the customer journey and the customer experience are closely related to brand-related issues. For Ndhlovu and Maree (2023), brand-related issues in a technological context have a significant impact not only on customer compliance, but also on their future intentions. In accordance with Erdem and Swait (2004), brand trustworthiness, as a sub-construct of brand credibility, has a direct impact on consumer choices. Going further, and specifically in the context of use of VASAI, Jain et al. (2022) suggest that brand credibility can influence the overall perceived value in the use and use intention of the assistant. This leads to the last hypothesis of the structural model:

H7. *Brand credibility has a positive effect on continued use intention.*

2.2. Moderating effect of Brand loyalty

The final construct examined in the study is brand loyalty. In previous research, brand loyalty has been defined as a consumer's tendency to choose the same brand over other brands among available options in the market (Hasan et al., 2021; Jacoby and Chestnut, 1978). In the context of VASAI, the construct of brand loyalty has typically been treated as a dependent variable (Hasan et al., 2021; Maroufkhani et al., 2022). Studies such as Hasan et al. (2021) or Maroufkhani et al. (2022) have already served to confirm that several aspects related to the use of VASAI influence brand loyalty. Having already confirmed these relationships, in the present research the author opts for a slightly different approach by analyzing the moderating effect of brand loyalty in the structural model.

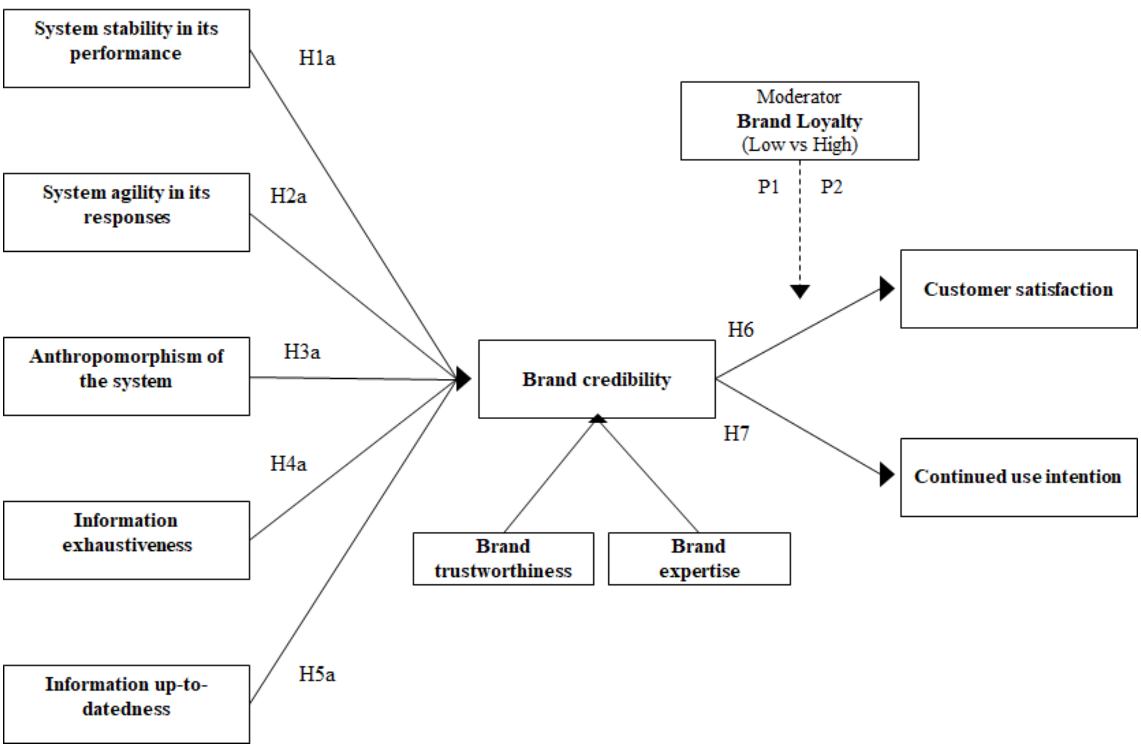
Ramachandran and Balasubramanian (2020) indicate that brand loyalty has a moderating effect on technological services and products. According to Brakus, Schmitt, and Zarantonello (2009), brand-related constructs can influence loyalty towards the firm. On the other hand, Brakus et al. (2009) postulate that when there are similarities between brand personality traits and customer personality traits, brand-related constructs have an impact on consumer satisfaction. Likewise, Delgado-Ballester and Munuera-Alemán (2001) address that in a high involvement brand-to-customer relationship, brand-related constructs affect customer satisfaction. Along the same lines, previous research also shows the existence of relationships between customer loyalty and consumers' future intentions; whether they are purchase intentions or intentions at the relational level (Amoroso and Lim, 2017; Nazarian et al., 2023). In light of the above, the author postulates that brand loyalty is a moderator of the strength of the relationship between brand credibility (based on brand trustworthiness and brand expertise) and customer satisfaction, on the one hand, and continued use intention, on the other. The author possess the following moderating proposals:

P1: *The relationship between brand credibility and customer satisfaction is stronger in high brand loyalty situations than in low brand loyalty situations.*

P2: *The relationship between brand credibility and continued use intention is stronger in high brand loyalty situations than in low brand loyalty situations.*

Figure 1 shows the set of hypotheses and the overall structural model proposed by the author.

Figure 1. Proposed structural model.



Source: Own elaboration

3. Methodology

3.1. Sampling procedure

The author selected a sample of participants from Singapore because of the proliferation of AI-based technologies in the country's industrial fabric and the particular importance of these technologies in its society. In the case of Singapore, both the government and business associations have expressed the need to explore the factors that influence the use of information systems supported by these technologies (Karippur et al., 2020; Zulaikha et al., 2021). An online questionnaire was administered in the social network LinkedIn through the most relevant professional groups of this country within the platform. The subjects gave their informed consent and confirmed that their participation in the study was voluntary. As an incentive, and in line with similar research in digital contexts, all participants were eligible to receive a $200 Amazon gift card at the end of the study (Birnholtz et al., 2004).

Consistent with common practice, the author used a non-probability sampling strategy, targeting people who had used VASAI at least once in the past year. The data was collected from May to July 2023. The sample size for the study, consistent with previous marketing research, was calculated with G*Power software, version 3.1.9.7. (Maroufkhani et al., 2022; Silva et al., 2014).

According to G*Power 3.1.9.7, the minimum required sample size had be greater than or equal to 501 respondents, with $f^2 = 0.15$ (effect size), $\alpha = 0.05$ (probabilistic error type 1), $\beta = 0.10$ (probabilistic error type 2). The total sample obtained, of 651 participants, was large enough to test the structural model according to the criteria described above and the statistical analysis strategy used. Although this sample size may be modest in the context of other research, it was more than substantial in the case of studies on AI-based assistants, and exceeded the sample sizes of similar studies such as those by Chhikara et al. (2022), Molinillo et al. (2023), Ghazali et al. (2023), or Maroufkhani et al. (2022). Studies with samples of 237, 250, 345, and 426 subjects, respectively.

3.2. Operationalization of constructs

The questionnaire had thirty-seven items distributed in the constructs indicated in the structural model (see Figure 1). The structural model considered regular constructs, but also brand credibility as a second-order construct. Following the postulates of previous research (Erdem and Swait, 1998; Jain et al., 2022), the brand credibility construct was formed from the sub-constructs of brand trustworthiness and brand expertise.

All the items of the instrument were presented using a 5-point Likert scale, from 1 ("Strongly disagree") to 5 ("Strongly agree"). The questionnaire items were constructed from the conceptual proposals made by different authors in previous research in the fields of AI-based technologies and marketing. The constructs of system stability, system agility, anthropomorphism, information exhaustiveness, and information up-to-datedness were adapted from Wixom and Todd (2005), Moussawi et al. (2021), and Ghazali et al. (2023). The constructs of brand trustworthiness and brand expertise were designed based on the work of Featherman et al. (2021), and Ghazali et al. (2023). The customer satisfaction and continued use intention constructs were elaborated based on the studies of Bhattacherjee (2001), and Davis et al. (1989). Finally, the brand loyalty construct was adapted from Hasan et al. (2021), and Jacoby and Chestnut (1978). See Appendix for details on the items in each construct.

3.3. Analysis and evaluation of the structural model

The evaluation of the model proposed by the author was carried out in two distinct phases. First, the validity and reliability of the instrument were examined, using the usual indicators, in addition to the HTMT criterion (Heterotrait- Monotrait Ratio of Correlations) and the Fornell-Larcker criterion. The structural model was then evaluated to test the proposed relationships between constructs. For this purpose, the researcher opted for structural equation modeling using the partial least squares technique (PLS-SEM). PLS-SEM analysis provided a robust approach widely accepted in the field of marketing research (Amoah and Jibril, 2021; Molinillo et al., 2023; Sharma et al., 2023). The author conducted the analyses using Smart PLS software version 3.3.7.

Since the researcher considered the construct of brand credibility as a second-order construct formed from the first-order constructs, or formative sub-constructs, of brand trustworthiness and brand expertise, the latent scores of these two sub-constructs were used to arrange the main construct. This method, also called the higher-order construct system, expands the conceptualization of constructs while reducing the number of paths in the theoretical model, improving its parsimony (Sarstedt et al., 2019). The remaining eight constructs of the model (system stability, system agility, anthropomorphism, information exhaustiveness, information up-to-datedness, customer satisfaction, continued use intention, and brand loyalty) were used as first-order constructs and were represented by their own scores in the analysis.

Before the analysis, since data were collected using a survey instrument, common-method bias was assessed to ensure that correlations between constructs were not significantly influenced by the measurement instrument. Common-method bias, in line with similar research (Jain et al., 2022; Molinillo et al., 2023), was tested in two different ways: the Harman Single-Factor (Podsakoff et al., 2003) and the Common Latent-Factor (Eichhorn, 2014). The Harman Single-Factor technique uses factor analysis in which all variables load on a single factor and are not constrained by rotation (Podsakoff et al., 2003). The results showed that 29.45% of the variance was explained by a single factor. The explained variance value below 50% confirmed that there was no common-method bias. Similarly, the Common Latent-Factor technique estimates the common variance as the square of each common factor in each path (Eichhorn, 2014). The results showed that the maximum common variance was also below the 50% threshold, again confirming the absence of common-method bias in the study.

4. Results

The results showed that 58.99% of the respondents were male and 41.01% were female. Similarly, 71.43% of the participants were 35 years old or older. Most of the respondents had a university degree, either a bachelor's (50.08%) or a Master's degree (20.28%) (Table 2).

Table 2. Descriptive statistics of participants characteristics (n = 651).

		Frequency	%
Gender	Man	384	58.99%
	Woman	267	41.01%
Age	18-24	67	10.29%
	25-34	119	18.28%
	35-44	134	20.58%
	45-54	182	27.96%
	>54	149	22.89%
Education level	Basic studies	182	27.96%
	Bachelor's degree	326	50.08%
	Postgraduate degree	132	20.28%
	PhD	11	1.69%
VASAI most used	Xiao AI (Xiaomi)	189	29.03%
	Bixby (Samsung)	171	26.27%
	Siri (Apple)	100	15.36%
	Google Assistant (Google)	95	14.59%
	Alexa (Amazon)	52	7.99%
	Cortana (Microsoft)	28	4.30%
	Ivi, Genie, and other website assistants	16	2.46%
Previous time of use of VASAI	<1 year	182	27.96%
	1-2 years	160	24.58%
	2-4 years	158	24.27%
	>4 years	151	23.20%
Frequency of VASAI use	At least once a day	197	30.26%
	At least once a week	184	28.26%
	Between 2-3 times a month	270	41.47%

Source: Own elaboration

Respondents were also asked which VASAI they used most often, for how long, and how often. It was found that 29.03% of respondents used Xiaomi's Xiao AI, 26.27% used Samsung's Bixby, and 15.36% used Apple's Siri. Meanwhile, 2.46% used lesser-known systems such as Ivi, and Genie and other website assistants. In terms of usage experience, 27.96% had been using VASAI for less than a year, while 23.20% had been using these technologies for more than four years. Finally, in terms of frequency of use, 30.26% used VASAI at least once a day (see Table 2).

4.1. Validity and reliability of the structural model

Firstly, the researcher conducted an Exploratory Factor Analyses (EFA) to examine the validity and reliability of the instrument as a whole, confirming that the questionnaire was able to explain 69.23% of the variance in the structural model, also showing a general Cronbach's alpha (α) of 0.897.

Thirty-three of the thirty-seven items in the instrument had outer loadings greater than .700, confirming the appropriateness of these questions (see Table 3). In contrast, in four of the thirty-seven items, questions SAR3, ANS3, CSA4, and CUI4, the outer loadings were below 0.700. Therefore, these items (SAR3, ANS3, CSA4, and CUI4) were removed to improve the internal consistency of the constructs (Ghazali et al., 2023).

Similarly, the average variance extracted (AVE) in the all the constructs was greater than 0.500, indicating that the measurement model had convergent validity. The composite reliability (CR) and Cronbach's alpha (α), in each construct, also exceeded the threshold of 0.700, indicating that the model was highly reliable (Mohd Razali and Bee Wah, 2011).

Table 3. Descriptive and validity indicators of the structural model.

	Construct	Item Code	Outer loadings	Mean	SD	α	CR	AVE
1	System stability in its performance	SSP1	0.915	3.43	1.069	0.819	0.972	0.892
		SSP	0.910	2.81	1.286			
		SSP3	0.944	3.23	1.082			
2	System agility in its responses	SAR1	0.957	3.64	1.142	0.829	0.948	0.870
		SAR2	0.913	3.53	1.092			
		SAR3	0.652	3.13	1.181			
3	Anthropomorphism of the system	ANS1	0.954	3.23	1.125	0.827	0.911	0.874
		ANS2	0.927	3.03	1.214			
		ANS3	0.558	3.49	1.058			
4	Information exhaustiveness	IEX1	0.874	3.49	0.837	0.852	0.907	0.772
		IEX2	0.837	3.42	1.056			
		IEX3	0.842	3.12	1.198			
5	Information up-to-datedness	IUD1	0.759	3.09	1.258	0.932	0.972	0.804
		IUD2	0.902	3.06	1.222			
		IUD3	0.874	2.58	1.538			
6.1.	Brand credibility (Brand trustworthiness)	BTR1	0.758	3.37	1.068	0.857	0.972	0.882
		BTR2	0.913	3.19	1.192			
		BTR3	0.944	3.10	1.177			
		BTR4	0.949	3.20	1.293			
		BTR5	0.917	2.96	1.217			
6.2.	Brand credibility (Brand expertise)	BEX1	0.807	2.50	1.786	0.938	0.942	0.854
		BEX2	0.798	3.53	1.096			
		BEX3	0.834	3.25	1.117			
		BEX4	0.925	3.38	1.118			
		BEX5	0.931	3.37	1.126			
7	Customer satisfaction	CSA1	0.924	3.21	1.407	0.919	0.948	0.870
		CSA2	0.953	3.69	1.099			
		CSA3	0.927	3.80	1.053			
		CSA4	0.449	3.81	1.041			
8	Continued use intention	CUI1	0.874	3.75	1.051	0.847	0.911	0.874
		CUI2	0.827	3.84	1.065			
		CUI2	0.842	3.83	1.009			
		CUI4	0.519	2.84	0.968			
9	Brand loyalty	BLO1	0.903	3.71	1.118	0.845	0.798	0.873
		BLO2	0.953	1.79	1.099			
		BLO3	0.927	1.80	1.041			

Source: Own elaboration

Abbreviations: SD - Standard Deviation / α - Cronbach's alpha / CR - Composite Reliability / AVE - Average Variance Extracted.

Since the structural model considered the analysis of brand credibility (construct 6) as a second-order construct, the validity and reliability of the items that serve as first-order or formative sub-constructs were also assessed. According to the observations in Table 4, the results were valid and reliable (Sarstedt et al., 2019). All the first-order constructs, or formative sub-constructs, had significant positive relationships with second-order constructs. Furthermore, in line with Hair, Hult, Ringle, and Sarstedt (2017), potential multicollinearity between the first-order constructs, or formative sub-constructs, was examined using the variance inflation factor (VIF). The observed VIF values of 2.593 and 1.679, both below the threshold of 3.3, indicated that there was no significant multicollinearity between the items that make up the brand credibility construct (construct 6) and, consequently, that the effects of the coefficients could be satisfactorily interpreted separately (see Table 4).

Table 4. Assessment of first-order constructs or formative sub-constructs.

Second order constructs	First order constructs	Outer weights	*p-valuer*	Outer loadings	*p-value*	VIF
6 Brand credibility	6.1. Brand credibility (Brand trustworthiness)	0.415	.008	0.813	.000	1.679
	6.2. Brand credibility (Brand expertise)	0.397	.011	0.894	.000	2.593

Source: Own elaboration

Abbreviation: VIF - Variance inflation factor.

The discriminant validity of the structural model was examined using two methods: the Heterotrait- Monotrait Ratio of Correlations (HTMT) criterion (Voorhees et al., 2016) and the Fornell-Larcker criterion (Amoah and Jibril, 2021). As can be seen in Table 5, most of the HTMT coefficients were below the conservative threshold of 0.750, which according to different authors (Voorhees et al., 2016), indicated that the discriminant validity was fully satisfactory.

Table 5. Correlations under HTMT criterion.

	Construct	1	2	3	4	5	6	7	8	9
1	System stability in its performance	-								
2	System agility in its responses	0.604	-							
3	Anthropomorphism of the system	0.615	0.701	-						
4	Information exhaustiveness	0.726	0.764	0.407	-					
5	Information up-to-datedness	0.760	0.632	0.426	0.451	-				
6	Brand credibility	0.423	0.513	0.603	0.215	0.368	-			
7	Customer satisfaction	0.641	0.512	0.487	0.398	0.301	0.279	-		
8	Continued use intention	0.714	0.645	0.594	0.372	0.473	0.378	0.477	-	
9	Brand loyalty	0.623	0.593	0.553	0.425	0.401	0.227	0.323	0.279	-

Source: Own elaboration

Similarly, Table 6 shows the results of correlations according to the Fornell-Larcker criterion. The results showed that the square root of the AVE values of all constructs (bold values above the diagonal) were greater than the values of their column for each construct (values below the diagonal), thus confirming, again, the discriminant validity of the structural model (Hair et al., 2019).

Table 6. Correlations under Fornell-Larcker criterion.

	Construct	1	2	3	4	5	6	7	8	9
1	System stability in its performance	**0.882**								
2	System agility in its responses	0.735	**0.801**							
3	Anthropomorphism of the system	0.615	0.751	**0.765**						
4	Information exhaustiveness	0.752	0.855	0.607	**0.786**					
5	Information up-to-datedness	0.750	0.572	0.725	0.751	**0.765**				
6	Brand credibility	0.632	0.502	0.702	0.615	0.553	**0.657**			
7	Customer satisfaction	0.751	0.5692	0.637	0.613	0.701	0.571	**0.876**		
8	Continued use intention	0.805	0.578	0.615	0.672	0.572	0.573	0.677	**0.765**	
9	Brand loyalty	0.612	0.712	0.672	0.625	0.501	0.627	0.622	0.571	**0.712**

Source: Own elaboration

The results obtained, with both methods, served to corroborate that all the constructs achieved the desired discriminant validity and, consequently, that all variables were empirically different and could be considered, in such a way, in the evaluation of the model (Hair et al., 2019).

4.2. Model evaluation and hypothesis testing

Once the discriminant validity was established, the structural model was assessed to examine the connections among the constructs. Using 5000 iterative subsamples, the bootstrapping technique was applied in the PLS-SEM. The coefficient of determination (R^2) was employed to assess the model's explanatory power. The results showed that the values of all the constructs were in the range of R^2 values from 0.501 to 0.593 (System agility, $R^2 = 0.511$ / Brand trustworthiness, $R^2 = 0.593$) thus indicating that the amount of variance explained for each construct by another construct was between 51.1% and 59.3%. Consistent with previous studies (Hair, Ringle, and Sarstedt, 2014; Henseler, Ringle, and Sinkovics, 2009) R^2 coefficients between 0.500 and 0.750 indicated acceptable variance explained by the model.

The analyses reveal that system stability, system agility, and anthropomorphism, as indicators of system quality; do not have an impact on the brand credibility construct (H1, H2, and H3). In contrast, the results show that the constructs of information exhaustiveness and information up-to-datedness have an effect on the construct of brand credibility. Thus, the hypotheses H4 and H5 are confirmed with β values of 0.211 and 0.255 respectively, and p-values below .05 in both cases; corroborating that information exhaustiveness and information up-to-datedness, as indicators of information quality, affect brand credibility.

In the second part of the model, examining how brand credibility affects customer satisfaction and continued use intention (H6 and H7), results show that brand credibility has a significant effect on these two constructs. Thus, hypotheses H6 and H7 are supported. The respective β values of 0.289 and 0.304, along with the *p*-values below .001 in both cases, confirm the aforementioned hypotheses.

Table 7. Results of the hypotheses testing.

Hypothesis	Path in the structural model	β standard	SD	*t*-value	*p*-value	Supported
H1	System stability in its performance → Brand credibility	0.060	0.109	0.693	.417	No
H2	System agility in its responses → Brand credibility	0.023	0.096	0.584	.150	No
H3	Anthropomorphism of the system → Brand credibility	0.098	0.087	0.072	.111	No
H4	Information exhaustiveness → Brand credibility	0.211	0.082	3.471	<.01**	Yes
H5	Information up-to-datedness → Brand credibility	0.255	0.111	4.160	<.05*	Yes
H6	Brand credibility → Customer satisfaction	0.289	0.109	9.293	<.001***	Yes
H7	Brand credibility → Continued use intention	0.304	0.187	7.071	<.001***	Yes

Source: Own elaboration

Note: 95% confidence level - two-tailed: / *$p < .05$; **$p < .01$; ***$p < .001$

4.3. Moderating effect of Brand loyalty analysis

Finally, the author examined the moderating effect of brand loyalty on the strength of the relationships between brand credibility and customer satisfaction (P1); and brand credibility and continued use intention (P2). Following previous studies, the author evaluated the moderating effects of brand loyalty in both paths using a multigroup analysis (MGA) with up to 5000 iterative subsamples (Huang and Yu, 2023; Molinillo et al., 2023). The researcher used the method recommended by Jain et al. (2022) to assess brand loyalty, as it was a continuous variable measured by items on a 5-point Likert scale. The sample was divided into two groups: low brand loyalty, with scores below the mean, and high brand loyalty, with scores above the mean. This made it possible to assess how the moderating influence of brand loyalty varied depending on whether brand loyalty was high or low in each path. Table 8 shows the results of the MGA, which confirms the P1 proposed for path H6 (β = 0.044 and p-value < .01), and the P2 postulated for path H7 (β = 0.065 and p-value < .01).

Table 8. MGA moderating effect (Low brand loyalty vs High brand loyalty).

Proposition	Path in the structural model	Low brand loyalty (β)	p-value	High brand loyalty (β)	p-value	Comparison	Significant difference
(P1) for H6	Brand credibility → Customer satisfaction	0.044	.09	0.481	.01**	3.174	Yes
(P2) for H7	Brand credibility → Continued use intention	0.065	.22	0.586	.01**	3.235	Yes

Source: Own elaboration

Note: *p < .05; **p < .01; ***p < .001

Complementary to the MGA, and in line with Liébana-Cabanillas et al. (2014), the researcher conducted a second analysis of the moderating effect of brand loyalty in IBM SPSS 29.0. In this case, to divide the sample into the two groups (high brand loyalty and low brand loyalty), the researcher, following Liébana-Cabanillas et al. (2014), performed a measurement test of invariance by comparing the degrees of freedom through a Chi-square (χ^2), which showed significant differences. After determining the existence of significant differences between the two groups, the author used a modified Student's t test for independent samples to compare the regression coefficients or weights (Lee et al., 2005). The results in Table 7 corroborated the P1 suggested for path H6 (β = 0.101 and p-value < .01), in addition to the P2 proposed for path H7 (β = 0.122 and p-value < .01).

Table 9. Student's t test moderating effect (Low brand loyalty vs High brand loyalty).

Proposition	Path in the structural model	Low brand loyalty (β)	p-value	High brand loyalty (β)	p-value	t-test	Significant difference
(P1) for H6	Brand credibility → Customer satisfaction	0.101	.17	0.514	.01**	3.174	Yes
(P2) for H7	Brand credibility → Continued use intention	0.122	.12	0.498	.01**	3.235	Yes

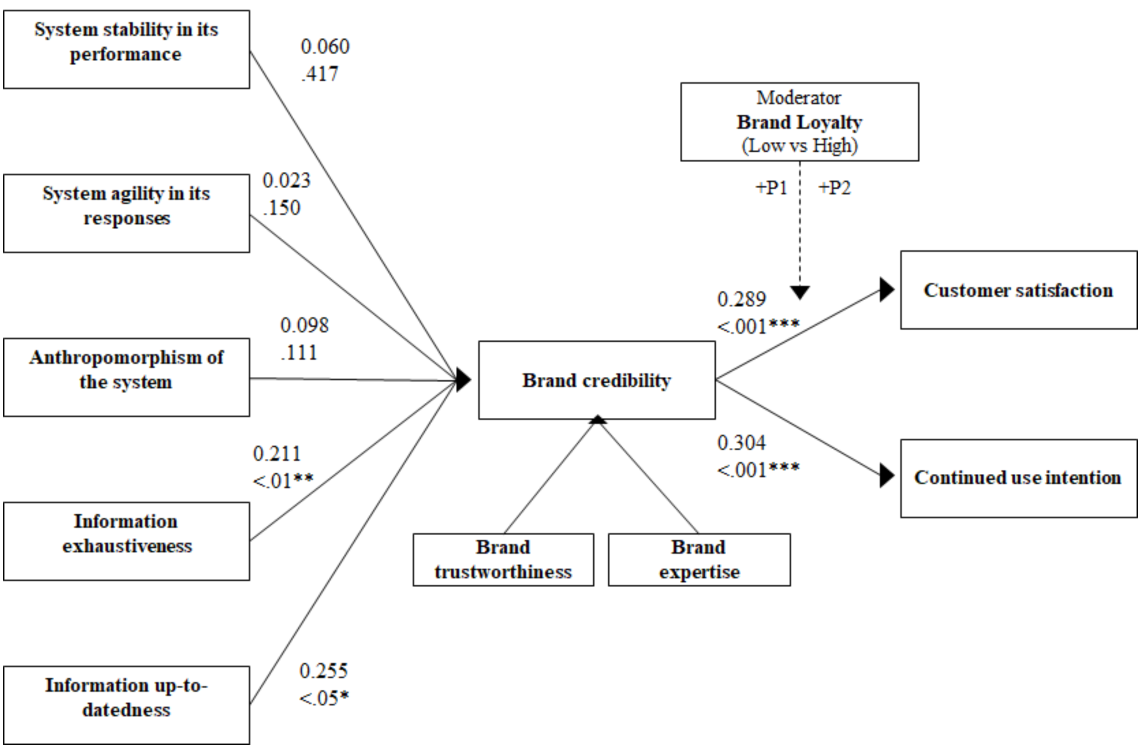
Source: Own elaboration

Note: *p < .05; **p < .01; ***p < .001

Based on the data presented in Tables 8 and 9, it can be concluded that brand loyalty moderates the strength of the relationship between brand credibility and customer satisfaction and, as well as the relationship between brand credibility and continued use intention. This confirms the moderating effects P1 and P2 proposed by the author for the paths hypothesized in H6 and H7. In both scenarios, the paths between brand credibility and customer satisfaction, on the one hand, and continued use intention, on the other, are influenced by brand loyalty in high loyalty situations. This suggests that the influence of brand credibility on these two constructs is stronger when brand loyalty is higher.

Figure 2 displays the author's proposed structural model, including β standard, significance values, rejected and supported hypotheses, along with their respective values.

Figure 2. Structural model hypothesis testing results.



Source: Own elaboration

5. Discussion

The results obtained show that neither the stability of the VASAI in its performance, nor its agility in providing answers, nor its anthropomorphic characteristics influence the brand credibility. This is contrary to previous studies, such as those of Chen and Park (2021) or Ghazali et al. (2023), which address that brand-related constructs are conditioned by the attributes related to the quality of the system. Ghazali et al. (2023) point out that the overall system quality conditions specifically brand trustworthiness (as a sub-construct of brand credibility). In the same vein, Chen and Park (2021) suggest that the anthropomorphic characteristics of the VASAI may have an impact on consumer trust constructs.

The author believes that the discrepancy between the results of the current study and the positive effects found in previous research (Chen and Park, 2021; Ghazali et al., 2023) may be due to the rapid and continuous evolution of these technologies. In a short period of time, both VASAI and users' perceptions of these technologies have evolved on several levels. Features related to system quality, which were once a differentiating component in the VASAI evaluation, are now considered basic aspects and do not, in themselves, represent a differentiating value. Today, it is rare for VASAI to present problems such as service interruptions, slow response times, or inconvenience in use that could have a negative impact on the customer's attitude toward the brand. All of this may justify the fact that, at the present time, and after the technical progress experienced, the elements related to system quality have become basics and do not affect the usability of the system (Gao and Waechter, 2017) or its technical robustness (DeLone and McLean, 2014), and therefore do not influence the customer's attitude towards the system and its brand.

On the other hand, the findings reveal that aspects associated with information quality, such as information exhaustiveness or information up-to-datedness, are conditioning factors of brand credibility. This is consistent with the findings of Jain et al. (2022) in their study on brand credibility and privacy risks in interactive voice assistants. In this study, the authors show that the influence of the utilitarian features in the VASAI -such as information quality- on the perceived value of using the system is strongly conditioned by brand credibility. Thus, the ability of VASAI to provide comprehensive and up-to-date answers improves the user's attitude toward the brand. As a result, reliable information tends to satisfy consumer needs, which also promotes brand credibility.

However, the findings of the present research regarding the impact of information quality (information exhaustiveness and information up-to-datedness) on brand credibility also seem to contradict what was pointed out by Ghazali et al. (2023) in their study on the nexus between the instrumental aspects of VASAI and brand credibility. In this study, the authors suggest that information quality does not affect either brand trustworthiness or brand expertise, as sub-constructs of brand credibility. In the author's opinion, the differences observed in the results of these two studies may be due, again, to the rapid evolution of these technologies, but also to the sample of participants used in each investigation. While in the study by Ghazali et al. (2023), 79.40% of the respondents were under the age of 35, in the present study, it is essentially the opposite. In the present research, 71.43% of the participants were 35 years of age or older. This situation suggests that while information quality may not have an impact on brand credibility with a younger audience, it becomes a critical element with an older audience. That is, while for younger subjects, the aspects related to the usability of the VASAI (which is the case of the system quality mentioned above) have a greater impact on brand credibility than those related to the information quality; for older subjects the opposite may be true. That is, for an older audience, while the usability aspects of the VASAI would not affect brand credibility, the information quality aspects would.

Regarding the constructs of customer satisfaction and continued use intention, the results indicate that brand credibility influences both. The influence of brand credibility on customer satisfaction and usage intention is in line with the findings of Maroufkhani et al. (2022) in their study on how interactive voice assistants contribute to building loyalty, where the authors indicate that these technologies contribute positively to consumer satisfaction. As customer satisfaction increases, users are more likely to increase their engagement, thus strengthening the bond between the subject, VASAI, and the company, multiplying the user's intention to continue using the assistant (Lee et al., 2021). This seems to suggest that brands capable of offering high quality services may be perceived as stronger, thus increasing both customer satisfaction and the intention to continue using the system. Therefore, according to the findings, brand credibility is not only a determinant of customer satisfaction with the service, but also a driver of intention to continue using the VASAI.

Regarding the moderating effects examined, the findings show that brand loyalty has a moderating effect on the strength of the relationships between brand credibility and consumer satisfaction, on the one hand, and brand credibility and continued use intention, on the other, in high-loyalty situations. This suggests that the higher the level of brand loyalty, the greater the influence of brand credibility on these two constructs. These results support the observations made by Ramachandran and Balasubramanian (2020) in their investigation of technology product buyers. In this research, the authors confirm that brand loyalty has a moderating effect on post-use relationships such as attitude towards the brand and purchase intention. The results are also consistent with the findings of Amoroso and Lim (2017), who address that loyalty may have a mediating effect on consumer satisfaction.

6. Conclusions

6.1. Theoretical contributions

The present study extends the theoretical application of the ECM and the TP in the context of VASAI by integrating brand-related constructs (brand credibility and brand Loyalty) that allow a better understanding of the conditioning factors in customer satisfaction and continued use intention. The study shows that the constructs related to information quality condition the perception of brand credibility in VASAI, even more than the constructs associated to system quality, which have no effect. These findings seem to indicate that, after the continuous technical improvements of these assistants, aspects related to system quality seem to be taking a back seat at the moment, with information quality being a primary issue in the use of VASAI.

Likewise, the research reveals that brand credibility determines both customer satisfaction and the intention to continue using VASAI. Similarly, results show that brand loyalty also has a moderating effect on the relationships between brand credibility and consumer satisfaction, on the one hand, brand credibility and continued use intention, on the other. In this sense, the findings suggest that the relationship between brand credibility and these post-adoption attitudes is stronger in higher loyalty situations.

Consequently, the current study expands previous theoretical frameworks (such as TAM, UTAUT, ECM, or PT) by demonstrating the importance of brand management in shaping post-adoption behaviors in the use of VASAI. As a result, the research provides a deeper understanding of the brand-related issues that influence adoption and future intentions to use VASAI, thus providing a more comprehensive view of the dynamics of these technologies.

6.2. Managerial contributions

The ability of VASAI to provide information and recommendations has changed the way companies and brands interact with consumers. As previously mentioned, the ability of these technologies to provide personalized solutions has made VASAI key players in the customer journey and customer experience (Seeber et al., 2020). However, like any other AI-based technology, the success of VASAI depends on their capability to learn from user responses and improve these responses in the future. Therefore, the consolidation and success of VASAI depends directly on the consumer's satisfaction with the system and its continued use. Likewise, the consolidation and success of VASAI has important implications from a marketing analytics perspective. These implications can be of a strategic nature, for example, when it comes to the company's decision to use the technology rather than human beings to handle its interactions with consumers (Ma and

Sun, 2020). But, these implications could also be tactical or operational, such as optimizing customer service costs or readjusting the company's staff (Ashfaq et al., 2020).

The results of this study shed light on this topic, highlighting the importance of the correct management of brand-related issues, such as brand credibility or brand loyalty, in the development, consolidation, and success of these technologies. Consequently, the results of this research provide evidence that can be decisive, firstly, for the success of SAVIA and, secondly, for the definitive democratization of these technologies in the context of marketing, at the strategic, tactical, and operational levels.

On the other hand, the findings of this research also lead to reflection on the need to include in management teams marketers who have the necessary training to understand the nature and implications of using these AI-based technologies. But also marketers with multidisciplinary profiles, combining brand management and technical skills.

6.3. Limitations and future research

The present study has some limitations that future research should address to improve the robustness of the findings. First, although it is true that the author includes brand-related issues such as brand credibility or brand loyalty in the structural model, this research does not explore the incidence of other brand-related dimensions. Future research could consider the influence of aspects such as brand experience, brand affect, brand meaning, brand engagement, brand attachment, and brand familiarity in the use of VASAI.

Second, the quantitative methods used in this research may not account for the complexity of user attitudes and behaviors. To broaden the understanding of the effects found, qualitative methods such as focus groups and interviews should be included in future research.

Third, only VASAI constructs related to system quality and information quality are explored. To gain a more complete understanding of customer behavior when using VASAI, future research should include other variables such as privacy risk, security perceptions, or device design. Likewise, to determine their impact on the proposed model, future studies could examine the mediating effect of variables such as age or education level, as well as the moderating effects of factors such as eWOM or purchase intention.

Finally, it should be mentioned that the research only considers participants from one country. To make the results more globally applicable, future research should compare different cultures or include individuals from other nations. This type of comparative study could lead to a better understanding of the impact of brand-related issues on VASAI usage globally by highlighting potential cultural implications on usage patterns and preferences.

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Appendix

Table A. Constructs and items of the research instrument.

	Construct	Construct description	Item Code	Items	Sources
1	System stability in its performance	It refers to the safety, reliability, and continuity of the system in its operation.	SSP1	VASAI operates stably	Adapted from Wixom and Todd (2005), Moussawi et al. (2021), and Ghazali, Mutum, and Lun (2023)
			SSP2	VASAI performs tasks reliably	
			SSP3	VASAI operates continuously without interruptions	
2	System agility in its responses	It refers to the degree to which the user perceives that system provides timely responses.	SAR1	VASAI takes a long time to respond to my requests (- coded)	
			SAR2	VASAI provides information in a timely manner.	
			SAR3	VASAI responds to my requests quickly	
3	Anthropomorphism of the system	It refers to the degree to which the user perceives the system as human.	ANS1	VASAI is able to speak like a human being	
			ANS2	VASAI's behavior appears friendly	
			ANS3	VASAI's behavior is respectful	
4	Information exhaustiveness	It refers to the user's perception of the completeness of the information provided.	IEX1	VASAI provides a comprehensive set of information	
			IEX2	VASAI provides comprehensive information	
			IEX3	VASAI provides all the information I need	
5	Information up-to-datedness	It refers to the user's perception of how recent or up-to-date the information provided is.	IUD1	The information provided by the VASAI is the most recent	
			IUD2	The information provided by the VASAI is up to date	
			IUD3	The information provided by the VASAI is widely accepted	
6.1.	Brand credibility (Brand trustworthiness)	It refers to the user's perception that the brand is reliable, honest, sincere, and able to guarantee the quality of the product or service.	BTR1	Reliable (How do you perceive the brand?)	Adapted from Featherman et al. (2021) and Ghazali, Mutum, and Lun (2023)
			BTR2	Honest (How do you perceive the brand?)	
			BTR3	Sincere (How do you perceive the brand?)	
			BTR4	Secure (How do you perceive the brand?)	
			BTR5	Quality assurance (How do you perceive the brand?)	
6.2.	Brand credibility (Brand expertise)	It refers to how the user perceives the brand's competence at different touch points over time.	BEX1	Experienced (Perception of your interactions with the brand)	
			BEX2	Innovative (Perception of your interactions with the brand)	
			BEX3	Skilled (Perception of your interactions with the brand)	
			BEX4	Qualified (Perception of your interactions with the brand)	
			BEX5	Resolute (Perception of your interactions with the brand)	
7	Customer satisfaction	It refers to the psychological state of the user when the confirmed expectations are compared to the expected ones.	CSA1	I am very dissatisfied / very satisfied	Adapted from Bhattacherjee (2001) and Davis et al. (1989)
			CSA2	I am very displeased / very pleased.	
			CSA3	I am very frustrated / very happy	
			CSA4	I am absolutely disappointed / totally delighted	
8	Continued use intention	It refers to the user's intention to continue, or not, using the technology or the service.	CUI1	I plan to continue using VASAI	
			CUI2	My intention is to continue using VASAI on a regular basis	
			CUI2	I will continue using VASAI instead of using other alternatives	
			CUI4	I intend to increase my use of VASAI in the future	
9	Brand Loyalty	It refers to the consumer's tendency to choose one same brand rather than others (its competitors).	BLO1	Next time I purchase a product or service-related technology, I will choose the same brand, if the exits the option	Adapted from Hasan et al. (2021) and Jacoby and Chestnut (1978)
			BLO2	After using the VASAI, I consider myself loyal to the brand	
			BLO3	After using the VASAI, I intent to recommend the brand to others	

Source: Own elaboration