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RESEARCH ARTICLE

Exploring the Moderating Effect of Price on the Relationship Between Intention and Use of Voice Assistants

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Research Ethics Committee for Social Sciences, Humanities and the Arts.

ABSTRACT This study aimed to identify the moderating effect of price on the relationship between usage intention and the actual use of voice assistants. A quantitative approach was adopted, with a correlational scope and non-experimental, cross-sectional design. The sample consisted of 329 participants from Generations X, Y, and Z residing in various cities across Ecuador, selected through non-probability convenience sampling. Data were collected using a self-administered questionnaire comprising 26 items, measured on a five-point Likert scale. The questions were adapted from previously validated studies in the field of technology acceptance. Reliability tests, confirmatory factor analysis, and structural equation modeling were conducted using SmartPLS 4 software. The results showed that performance expectancy, effort expectancy, social influence, and facilitating conditions significantly influenced usage intention, which in turn had a direct impact on the actual use of voice assistants. Moreover, price positively moderates this relationship. Together, these findings offer an expanded theoretical model that addresses the previous gaps in the literature, providing a more comprehensive view of consumer behavior toward AI-based technologies.

INDEX TERMS Artificial intelligence, Ecuadorian consumers, UTAUT, voice assistants.

I. INTRODUCTION

The rapid advancement of technologies designed to optimize daily activities has fueled the development of Artificial Intelligence (AI) and its application in innovations, such as Voice Assistants (VAs) [1], [2]. These tools were created to perform tasks and respond to users' verbal queries, thereby facilitating interaction with digital devices [3]. Although VAs, commonly referred to as "Chatbot Technologies" is not a recent phenomenon, its evolution has significantly expanded its capabilities [4], [5]. Consequently, these assistants have become essential tools for improving efficiency in various day-to-day tasks [6], [7].

Conceptually, VAs are tools that utilize automatic speech recognition and natural language processing to enhance user experience with technological devices [3], [8]. These AI-based conversational agents allow users to interact using activation phrases such as "Alexa, change the music," to which the assistant responds in real-time by carrying out the requested action [9]. Consequently, VAs have begun to take on roles previously filled by friends, personal assistants, or subject matter experts [10].

The growing use of VAs by consumers has fueled the expansion of their global market, which has reached an

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estimated value of USD 3.564 billion by 2023, with a projected annual growth rate of 29.5% [11]. Furthermore, the number of users in the United States is expected to rise to 153.5 million by 2025 [12]. These figures highlight the significance of VAs in driving technological and economic transformation, which is considered one of the most important innovations since the launch of the iPhone [3]. From an economic standpoint, the VAs market is projected to reach USD 54.83 billion by 2033 [13].

According to research by Kim and Choudhury [14], approximately 98 million VAs-enabled devices were sold globally in 2019, and this number is expected to rise to 409.4 million by 2025. Despite this remarkable growth and optimistic outlook, conceptual and empirical research on VAs remains limited [3]. In particular, there is a lack of studies examining the impact of VAs on consumer behavior [10]. This research gap is largely due to the complex nature of VAs interactions, whose technological features differ significantly from those of other digital innovations such as mobile apps, websites, and smart devices [15].

Despite the growing interest in technology adoption, theoretical gaps remain in how traditional models, such as UTAUT and UTAUT2, account for economic factors like perceived price when explaining actual technology use. While these models effectively predict behavioral intention, they often fall short in explaining the transition from intention to action, especially in price-sensitive consumer environments. Furthermore, empirical studies rarely explore moderating variables that could bridge this gap, despite calls for more integrative models. This oversight limits theoretical development and practical application, particularly in contexts where price perception plays a central role in consumer decision-making. Along these lines, Fernandes and Oliveira [1] emphasized that understanding the factors influencing VA acceptance is still in its early stages, as most available studies have addressed the topic from a purely conceptual perspective.

VAs are reshaping consumer habits [4], as they not only facilitate task execution, but also transform the way users purchase products and interact with businesses [16]. For many users, the integration of VAs into mobile devices marked their first practical and meaningful experience with AI [17]. Some of the most popular mobile-based VAs include Apple's Siri, Amazon's Alexa, and Google Assistant [7]. Although research in this area has grown significantly over the past decade, studies exploring the acceptance of VAs among Ecuadorian consumers remain limited.

Given this context, various authors have stressed the importance of continuing to explore technology acceptance models [3], [10], particularly in developing countries [1], [16]. Specifically, there is a growing need to analyze the adoption of VAs such as Google Assistant, Siri, and Alexa [18]. In response to the aforementioned literature gaps, this study aimed to identify the moderating effect of price on the relationship between usage intention and actual use of VAs. To achieve this objective, the study addressed the following research questions: (a) What types of factors precede the intention to use voice assistants for daily activities? (b) How does usage intention influence the actual use of voice assistants in daily life? (c) How does price moderate the relationship between usage intention and actual use of voice assistants for daily activities?

Among the many factors that influence the translation of behavioral intention into actual usage, perceived price stands out as a key yet underexplored moderator, especially in contexts where affordability and value for money shape adoption decisions. The literature has long emphasized that when individuals evaluate a product or service, they weigh the perceived benefits against the associated economic cost. In the domain of technology acceptance, this evaluation often affects whether intention is transformed into actual usage, particularly for AI-based services that are still perceived as novel or optional. Price does not merely reflect monetary cost but also embodies perceived value, which can either facilitate or inhibit usage despite initial interest. Therefore, examining price as a moderating factor provides both a theoretically grounded and practically relevant extension to existing acceptance models.

The structure of this study is as follows. The first section presents the introduction and background of the research. The second section provides a literature review and discusses various models related to the acceptance of voice-activated devices and the theoretical framework supporting the study, including descriptions of the variables and hypotheses. The third section outlines the methodology, including the research design and statistical analysis. The fourth section focuses on the analysis and discussion of the results, including hypothesis testing. Finally, the fifth section presents the main conclusions, discusses the study's implications, and outlines its limitations.

This study contributes to the existing literature in three key ways. First, from a theoretical perspective, it extends the UTAUT framework by incorporating perceived price as a moderating variable, an aspect under-addressed in previous research on voice assistant adoption. Second, it offers a methodological contribution by testing this extended model using Structural Equation Modeling (SEM) with a generational sample from a developing country in Latin America. Third, from an empirical perspective, the study provides updated and contextualized evidence on the behavioral intentions and actual use of voice assistants among Ecuadorian consumers, thus filling a geographic and demographic gap in the literature.

II. LITERATURE REVIEW

A. UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) represents a comprehensive theoretical framework that emerged from the integration of several earlier theories and models on human behavior and technology adoption [16], [19], [20]. The development of the UTAUT was grounded in the integration of eight influential models that attempted to explain user acceptance of technology. These include the Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), Motivational Theory (MT), Social Cognitive Theory (SCT), the Technology Acceptance Model (TAM), and the PC Utilization Model [3]. For instance, TAM (an evolution of TRA and TPB) emphasized perceived usefulness and ease of use, but lacked explanatory power for certain social or facilitating factors. SCT contributed the notion of self-efficacy and environmental support, while the PC Utilization Model added behavioral context.

UTAUT, developed by Venkatesh et al. [21] proposes that an individual's intention to use a technology is conditioned by four core factors: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) [21], [22], [23].

In this study, UTAUT2 serves as a comprehensive lens for analyzing user behavior related to voice assistants. Its multidimensional structure allows for the examination of both rational and contextual influences, while the integration of perceived price as a moderating factor responds to recent calls for more nuanced modeling in technology acceptance research.

To align UTAUT with emerging consumer behavior trends, Venkatesh et al. [21] reviewed previous studies on consumer behavior and reformulated the original model, leading to the development of UTAUT2. This extension incorporated Hedonic Motivation as a new construct aimed at enhancing the understanding of extrinsic motivations that influence consumers. However, some scholars have questioned this extension, arguing that the model's average explained variance is high only when key relationships are moderated by four additional variables [24], [25]. Furthermore, McLean and Osei [16] suggest that, owing to the unique characteristics of AI-based technologies, these models may not fully capture the motivations behind the adoption and use of advanced technologies.

In light of these considerations, several recent studies have regarded UTAUT as a suitable theoretical model for identifying the antecedents influencing Usage Intention (UI) and the actual use of VAs [26], [27], [28]. Other studies have emphasized the need to incorporate new variables to construct more robust hypothetical models that enhance the understanding of consumer behavior in relation to technology use [29], [30], [31].

B. PERFORMANCE EXPECTANCY (PE)

PE is defined as the degree to which an individual believes that using a particular technology will help improve performance in specific tasks. This construct is directly linked to perceptions of usefulness and efficiency and has consistently been shown to be one of the strongest predictors of UI for technological devices [21], [32]. In the context of VAs use, PE translates into the perception that such technology enables users to perform tasks more efficiently, accurately, or innovatively. The greater this perception, the higher the user's predisposition to integrate technology into their daily routines. Previous research confirmed that PE influences UI in the adoption of technological devices [3], [33]. For example, Haugstvedt and Krogstie [34] demonstrated that PE plays a significant role in the UI of augmented reality applications in tourism settings. Similarly, Tao et al. [35] found that PE significantly influenced UI in mobile applications for hotel bookings.

In the context of artificial intelligence, Lu et al. [36] showed that PE affects customers' emotional responses toward AI devices, which in turn impacts their UI. Similarly, Kim et al. [3] confirmed that PE influences the UI of VAs in hotel rooms. To contribute further theoretical insights to this field of study, the following hypothesis is proposed:

H1. PE influences the UI of VAs for carrying out daily activities.

C. EFFORT EXPECTANCY (EE)

EE refers to perceived ease of use associated with a given technology. In other words, it encompasses factors, such as intuitiveness, accessibility, and the learning curve involved in using technological tools. According to Venkatesh et al. [21], this construct carries more weight during the initial stages of adoption when users are unfamiliar with the technology. In this regard, EE is a key factor that can shape UI for technological devices [3], [33], [34].

According to Al-Maskari and Sanderson [37], when users anticipate that achieving desired results will not require substantial effort, they experience a greater sense of control and confidence, which in turn motivates their intention to use a technology. Several studies have found that when users perceive technological applications as requiring minimal effort while providing clear utility, their satisfaction with such tools increases [38], [39], [40]. Similarly, other research has shown that EE significantly influences both perceived usefulness and UI, further reinforcing its important role in the adoption of technological tools [33], [41], [42], [43].

The influence of EE on UI remains debatable within the context of VAs. Moriuchi [32] argues that EE positively affects UI since users rely on VAs to complete daily tasks, while other researchers have found no significant impact of EE on UI of VAs [3]. To provide further empirical evidence and help clarify this discrepancy, the present study aims to test the following hypothesis:

H2. EE influences the UI of VAs for carrying out daily activities.

D. SOCIAL INFLUENCE (SI)

SI refers to the impact of significant others on an individual's decision to adopt or use a particular technology. This construct is especially relevant in environments with strong social norms, or where technology acceptance is influenced by social recognition [39]. In the case of VAs, recommendations from authority figures, colleagues, or opinion leaders can significantly foster UI, particularly when such actors endorse the usefulness of the technology [3].

Multiple studies have consistently demonstrated that SI plays a key role in shaping UI for various technologies. For instance, Morosan and DeFranco [44] found that hotel customers are influenced by social norms when deciding whether to use mobile payment applications. Similarly, Lu et al. [36] found that social group perceptions shape the UI of AI-enabled technological devices. Similarly, Roy et al. [33] concluded that positive feedback from family or friends strengthened users' perceptions of usefulness of AI-based devices within the hospitality industry, resulting in greater willingness to use them.

Recent studies, such as those by Yoon et al. [45] and Joe et al. [46], have found that users rely on their social environment judgment when deciding whether to adopt new technologies. Similarly, Kim et al. [3] identified that SI positively impacts the UI of VAs in the provision of hospitality services. To further contribute to the theoretical development of this research field, the following hypothesis is proposed.

H3. SI influences the UI of VAs for carrying out daily activities.

E. FACILITATING CONDITIONS (FC)

FC refers to users' perceptions of the availability of organizational, technical, and infrastructural resources that enable the effective use of a technology. Although in the original UTAUT model, this factor is more strongly associated with actual usage than with UI, its importance should not be underestimated. The availability of compatible devices, reliable connectivity, and technical support directly affect user experience and, consequently, influence the decision to continue using the technology over the long term [21].

The relationship between FC and UI has been widely explored in empirical studies, which generally agrees with its positive influence. For instance, Chang et al. [47] confirmed that in the hospitality industry, FC directly affects the UI of online booking systems. Similarly, Lu et al. [36] found that FC promotes the UI of AI-enabled technologies in restaurant services. Ambarwati et al. [48] also demonstrated that, in educational contexts, FC significantly influences the UI of online learning platforms. Taken together, these findings reinforce the idea that access to technical resources, information, and prior experience is a key factor in understanding user behavior regarding the adoption of new technologies [3]. In light of this and with the aim of contributing further empirical evidence to this field of study, the following hypothesis is proposed.

H4. FC influences the UI of VAs for carrying out daily activities.

F. USE INTENTION (UI)

UI is a central construct in technology adoption models and refers to the degree to which an individual consciously expresses willingness to use a specific technology in the future. This variable has been widely recognized as the most reliable predictor of actual system use, as proposed by the UTAUT model [21]. In this sense, UI not only helps to understand users' perceptions of a technology, but also the factors that motivate or inhibit its adoption [15].

According to Chang et al. [47], most studies on technology use have employed UTAUT to identify the UI as part of the initial adoption process. However, research on both the initial adoption and continuous use of VAs remains scarce [49], highlighting the need to respond to recent calls for studies that focus on next-generation technologies, such as AI-based VAs [50], especially tools such as Google Assistant, Siri, and Alexa [18]. Understanding UI in the context of VAs is therefore essential for anticipating technology adoption patterns, particularly in developing countries, where factors such as access, cost, and digital literacy can significantly shape both UI and actual use of VAs [16], [18].

H5. UI influences the actual use of VAs for carrying out daily activities.

G. PRICE (PR)

Price, also referred to as perceived value [51], refers to the user's subjective evaluation of the economic sacrifice involved in acquiring, implementing, or using technology [31], [52]. Therefore, it is not solely about the monetary value expressed in numbers but also about relative value, that is, the user's assessment of what they pay in relation to the benefits they expect to receive [53]. According to Almaiah et al. [54], price reflects a user's intellectual trade-off with the perceived benefits of a technology.

Although several studies have confirmed the influence of price on UI for technological devices [55], [56], [57], the literature reveals that the moderating effect of price on the relationship between UI and actual use of VAs has not yet been explored. Kim et al. [3] called for future research to broaden its scope by examining additional factors such as users' willingness to pay for VAs. Based on these considerations, the present study aimed to test the following hypotheses:

H6. Price moderates the relationship between UI and the actual use of VAs in daily activities.

H. RESEARCH MODEL

Based on the theoretical and conceptual framework outlined above and in response to one of the future research recommendations proposed by Kim et al. [3], this study adopts the UTAUT model and introduces price as a moderating variable, proposing a new hypothetical model aimed at identifying the moderating effect of price on the relationship between UI and the actual use of VAs (See Figure 1).

III. METHODOLOGY

A. INSTRUMENT DESIGN AND DATA COLLECTION

This study was conducted using a quantitative research approach with a correlational scope and non-experimental,

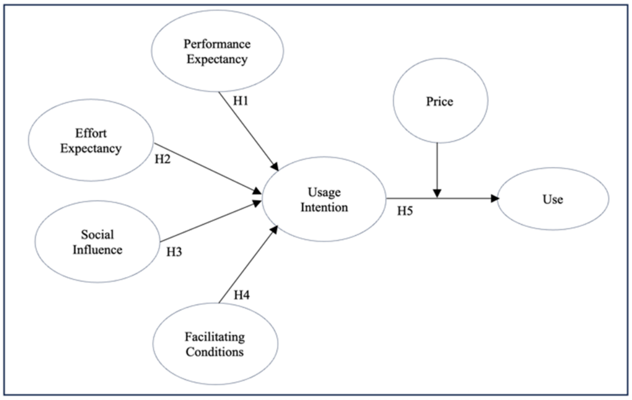

FIGURE 1. Hypothesized model.

cross-sectional design. Data were collected through a self-administered questionnaire consisting of 26 items (four demographic questions and 22 questions designed to measure the variables in the hypothesized model) using a 5-point Likert scale, where 5 indicated "strongly agree" and 1 indicated "strongly disagree". Regarding survey language adaptation, the original measurement items were developed in English and subsequently translated into Spanish to align with the linguistic context of Ecuadorian participants. To ensure semantic and conceptual equivalence, a back-translation procedure was employed. The items were first translated into Spanish by a bilingual researcher and then independently translated back into English by another bilingual expert. The two English versions were compared to resolve discrepancies and confirm that the translated items retained their original meaning and theoretical alignment.

Prior to implementation, the questionnaire was validated by a panel of experts, including two researchers and two information technology professionals. No modifications to the instrument were suggested by the panel. Additionally, the instrument underwent a pilot test with 30 self-identified VAs users. The survey items were adapted from high-impact articles in the current field of study (See Appendix A).

To ensure methodological rigor in the data collection process, a non-probability convenience sampling method was applied. Participants were selected based on their prior or current use of voice assistants and were recruited primarily through academic mailing lists, institutional WhatsApp groups, and targeted posts on social media. The questionnaire was self-administered online using Google Forms, which allowed for standardization and participant anonymity. Surveys were completed voluntarily and asynchronously in unsupervised environments, typically from the participants' homes or educational settings, using personal devices. This online format facilitated a broader geographical reach and higher accessibility. Data collection took place during a three-week period in early 2025.

The full survey was administered to 366 participants belonging to Generations X, Y, and Z, which were considered relevant target groups owing to their regular use of technology in daily life. However, only 329 responses were included in the final analysis, based on the inclusion criterion of current or prior use of VAs (Google Assistant, Siri, or Alexa). According to Hair et al. [58] a minimum of 10 observations per indicator or per structural path is advised for reliable estimation in reflective models. Given the model's complexity and the number of paths, the sample size of 329 exceeds these recommendations, ensuring adequate statistical power for the analysis. The sampling method was non-probabilistic, as the surveys were distributed online to university students in Ecuador's most populated cities (Santo Domingo, Quito, Guayaquil, and Cuenca), while also allowing participation from millennials and centennials residing in other cities across the country.

To reduce the potential for self-report bias, several procedural measures were implemented during survey design. Participants were assured of full anonymity and confidentiality, and participation was entirely voluntary. The questionnaire employed psychologically neutral wording and avoided evaluative or leading language. Additionally, items were grouped by construct but presented in a non-repetitive sequence to minimize response patterns and social desirability effects. These strategies aimed to foster honest and unbiased responses.

B. INTERNAL CONSISTENCY AND DATA ANALYSIS

To assess the internal consistency of the instrument, the reliability of the questionnaire was evaluated using Cronbach's alpha. According to the literature, item factor loadings should exceed a threshold of 0.70 [58]. Likewise, Cronbach's alpha values for each individual variable, as well as for the entire instrument, must surpass the 0.70 benchmark [59].

To validate the data, a Confirmatory Factor Analysis (CFA) was performed to assess the convergent and discriminant validity of the hypothesized model. According to several authors, convergent validity is confirmed when the Composite Reliability (CR) is greater than 0.70, and the Average Variance Extracted (AVE) exceeds 0.50, which is lower than the corresponding CR values [59], [60], [61].

To establish discriminant validity, the Square Roots of the AVEs (SRAVE) must be greater than the inter-construct correlations [62], [63]. Additionally, following the heterotrait-monotrait (HTMT) ratio criterion proposed by Henseler et al. [64], all HTMT values between the construct pairs must be below 0.90.

To assess potential common method bias (CMB), Harman's single-factor test was conducted using exploratory factor analysis. All measurement items were entered into an unrotated principal component factor analysis. The results revealed that the first factor accounted for 32.7% of the total variance, which is below the 40% threshold commonly used to indicate serious CMB concerns [65]. Therefore, it can be concluded that common method variance does not pose a significant threat to the validity of the study's findings. In addition, procedural remedies were implemented during survey design to mitigate bias, including ensuring participant anonymity, varying the item order, and adapting items from previously validated instruments.

IV. RESULTS

A. PARTICIPANTS' DEMOGRAPHIC CHARACTERISTICS

The demographic profile of the participants (n = 329) revealed diverse representation in terms of geographic location, educational level, age, and gender. Regarding city of residence, the largest proportion of respondents came from Santo Domingo de los Colorados (28.9%), followed by Guayaquil (22.2%), Quito (21.9%), Cuenca (11.2%), and 15.8% from other cities across Ecuador. In terms of educational level, a significant majority held undergraduate degrees (75.1%), whereas 24.9% had completed postgraduate studies. This suggests that the sample is largely composed of individuals with sufficient educational backgrounds to interact with advanced technologies, such as VAs.

Regarding age distribution, the dominant group consisted of centennials (born after the year 2000), which accounted for 39.8% of the total sample, followed by Younger Millennials (born between 1995 and 2000), representing 21.6%. This aligns with the literature, indicating that younger generations show a greater affinity toward adopting emerging technologies. In terms of sex, the sample presented a relatively balanced distribution, with a slight majority identifying as female (51.4%), male (47.7%), and 0.9% identifying with another sex. In reporting gender identity, the study categorized participants as "male," "female," and "other," following ethical standards of inclusivity and respect for diverse identities. This classification was presented in aggregate form to protect anonymity and avoid stigmatization. While the proportion of participants identifying as "other" was minimal, its inclusion acknowledges gender diversity and aligns with current research ethics guidelines.

This demographic distribution provides a solid foundation for analyzing perceptions, attitudes, and usage intentions regarding technologies such as Vas, particularly from the perspective of a young, urban, and educated population that is inclined to adopt technology to support their everyday activities (See Table 1).

TABLE 1. Demographic description.

Characteristic	Category	#	%
City	Santo Domingo de los Colorados	95	28.9%
	Quito	72	21.9%
	Guayaquil	73	22.2%
	Cuenca	37	11.2%
	Other cities in Ecuador	52	15.8%
Education level	Degree	247	75.1%
	Postgraduate	82	24.9%
Age range	1978 or earlier (Generation X)	31	9.4%
	Between 1979 to 1988 (Older Millennials)	61	18.5%
	Between 1989 to 1994 (Mid Millennials)	35	10.6%
	Between 1995 to 2000 (Younger Millenials)	71	21.6%
	After 2000 (Centennials)	131	39.8%
Gender	Male	157	47.7%
	Female	169	51.4%
	Other	3	0.9%
n= 329			

B. ESTIMATION OF THE MEASUREMENT MODEL

The hypothesized model, composed of seven variables (PE, EE, SI, FC, UI, PR, and US), was evaluated using CFA. Regarding convergent validity, the study confirmed that the factor loadings for each indicator and Cronbach's alpha exceeded the recommended threshold of 0.70. These results indicate factor loadings greater than 0.70 reflect a strong association between the items and the construct they are intended to measure. Additionally, a Cronbach's alpha above 0.70 suggests adequate internal consistency, meaning the items are reliable and consistently measure the same dimension [58], [59].

Furthermore, the study verified that the CR values (rho_a and rho_c) were above 0.70, and the AVE exceeded the 0.50 threshold while remaining lower than the corresponding CR values. These findings support the conclusion that the scales used in the model exhibit high internal consistency, confirming that the items reliably measured their respective constructs. The AVE analysis also demonstrates adequate convergent validity, as more than 50% of the variance of each construct is explained by its indicators. Moreover, the fact that the AVE is lower than the CR further confirms that the shared variance among the items exceeds the variance due to measurement errors [59], [60], [61].

Regarding discriminant validity, the study found that SRAVE was greater than the correlation values for each pair of constructs. This analysis demonstrates that each construct in the model is statistically distinct from the others, and that the items associated with each factor share more variance among themselves than with items from other constructs, thereby reinforcing the overall quality of the measurement model [60], [62], [63]. Additionally, when applying the HTMT ratio criterion, all values were below the threshold of 0.900, confirming the presence of discriminant validity among the constructs. This indicates that the evaluated dimensions are empirically distinct from one another [64]. Convergent and discriminant validity are shown in Tables 2 and 3, respectively.

C. STRUCTURAL EQUATION MODELING

After confirming the convergent and discriminant validity of the hypothesized model, SEM was conducted to evaluate the acceptance or rejection of the proposed hypotheses. Using the bootstrap method to assess causal relationships, we observed that the R^2 coefficients of the dependent variables exceeded the baseline threshold of 0.1. This confirms that the independent variables explain a significant portion of the variance in the dependent variables within the model (UI: 0.655; US: 0.466) [66].

TABLE 2. Convergen validity and realibility.

Variable	Item	Loading Factor	Cronbach's alpha	CC (rho_a)	CC (rho_c)	AVE
Performance Expectancy (PE)	PE1	0.806	0.807	0.814	0.874	0.634
	PE2	0.748				
	PE3	0.760				
	PE4	0.866				
Effort Expectancy (EE)	EE1	0.845	0.812	0.826	0.888	0.726
	EE2	0.817				
	EE3	0.893				
Social Influence (SI)	SI1	0.889	0.844	0.845	0.906	0.763
	SI2	0.866				
	SI3	0.865				
Facilitating Conditions (FC)	FC1	0.774	0.726	0.781	0.832	0.623
	FC2	0.776				
	FC3	0.817				
Usage Intention (UI)	UI1	0.891	0.858	0.858	0.913	0.779
	UI2	0.902				
	UI3	0.853				
Price (PR)	PR1	0.842	0.888	0.890	0.923	0.749
	PR2	0.887				
	PR3	0.887				
	PR4	0.846				
Use (US)	US1	1.000	1	1	1	1

TABLE 3. Discriminant validity.

Variable	PE	EE	SI	FC	UI	PR	US
PE	**0.797**	0.707	0.749	0.678	0.749	0.527	0.552
EE	0.568	**0.852**	0.488	0.828	0.894	0.679	0.601
SI	0.598	0.403	**0.873**	0.404	0.635	0.625	0.576
FC	0.544	0.666	0.345	**0.789**	0.712	0.479	0.503
UI	0.627	0.751	0.541	0.619	**0.882**	0.730	0.693
PR	0.446	0.579	0.541	0.445	0.638	**0.866**	0.605
US	0.499	0.542	0.529	0.460	0.641	0.571	**1.000**

Note(s): Fornell and Larcker diagonal; HTMT on the diagonal; Correlational values below the diagonal.

In addition, the Standardized Root Mean Square Residual (SRMR) value was below 0.07, indicating a good model fit and showing that the average discrepancy between the observed and predicted correlations was low. An SRMR: 0,07 value within the acceptable threshold (below 0.08) suggests that the model adequately represents the data and that the proposed theoretical relationships are consistent with empirical observations [58]. Finally, to determine the individual acceptance of each hypothesis, statistical significance was assessed. The analysis revealed that all six hypotheses proposed in the model were supported, as each yielded p-values < 0.05. Therefore, all six hypotheses are accepted. Table 4 presents the beta values and the hypothesis testing results.

V. DISCUSSION

To facilitate an understanding of the study's findings, the discussion is presented in three sections addressing the following research questions: (a) What types of factors precede the intention to use voice assistants for carrying out daily activities? (b) How does intention to use influence the actual use of voice assistants in carrying out daily activities? (c) How does price moderate the relationship between the intention and use of voice assistants in carrying out daily activities?

TABLE 4. Results hypothesis.

Hypotheses	Relation	β	p-values	Hypotheses
H1	PE-UI	0.149	0.009	Aceptado
H2	EE-UI	0.490	0.000	Aceptado
H3	SI-UI	0.206	0.000	Aceptado
H4	FC-UI	0.140	0.002	Aceptado
H5	UI-US	0.491	0.000	Aceptado
H6	PR(UI-US)	0.099	0.001	Aceptado

Use intention (R^2:0.655); Use (R^2:0.466); SRMSR: 0.07

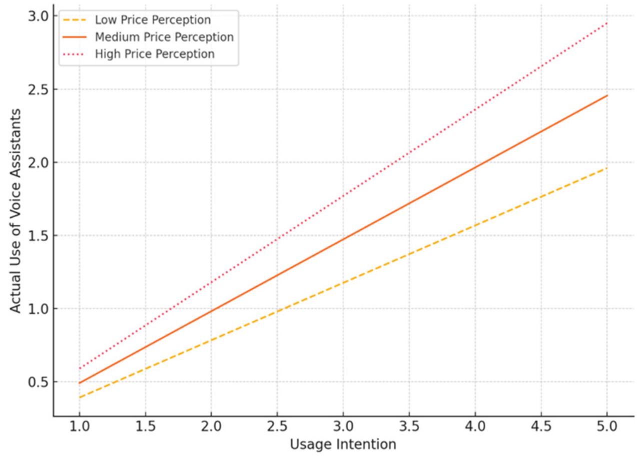

FIGURE 2. The figure illustrates the moderating effect of price on the relationship between usage intention and actual use of voice assistants.

A. ANTECEDENT FACTORS OF THE INTENTION TO USE VOICE ASSISTANTS

Hypothesis H1 was supported, with a coefficient of $\beta = 0.149$ and p-value <0.005, indicating a significant relationship between PE and the UI of VAs. This finding is theoretically justified by the UTAUT framework, which identifies PE as one of the primary predictors of technology adoption [21]. In the context of VAs, this influence is associated with users' perceptions that these tools help them perform tasks more efficiently, thereby increasing their willingness to adopt them [3], [32]. Previous studies have also demonstrated the importance of PE in everyday technologies, as shown by Tao et al. [35], who found the positive effects of PE on mobile applications for reservations and ordering. Consequently, acceptance of this hypothesis reinforces the idea that when users perceive VAs as enhancing their productivity or efficiency, they are more inclined to integrate them into their daily routines.

Hypothesis H2 was supported, with a coefficient of $\beta = 0.490$ and p-value <0.001, indicating a highly significant effect of EE on UI. This empirical result aligns with the theoretical foundations of UTAUT, which considers EE a key factor in the early stages of technology adoption [21]. The literature supports this relationship, as various authors argue that lower perceived difficulty in using technology facilitates its adoption [37], [38]. Moriuchi [32] specifically emphasized that VA users value the ability to perform actions with minimal cognitive or technical effort, which positively influences their intention to use. Therefore, this result confirms that the simpler and more accessible a VA is perceived as, the higher its acceptance among users.

Hypothesis H3 was statistically supported, with a coefficient of $\beta = 0.206$ and p-value < 0.001, showing a significant influence of SI on UI. This finding aligns with prior literature that recognizes SI as a key component in shaping technology-related attitudes, particularly when decisions are influenced by social norms or external validation [36], [44]. Studies by Roy et al. [33] and Joe et al. [46] confirm that recommendations from influential individuals such as friends, family members, or authority figures directly impact perceived usefulness and willingness to adopt AI-based technologies such as VAs. Thus, the acceptance of this hypothesis demonstrates that technology adoption decisions do not occur in isolation but are strongly influenced by the user's social environment.

Hypothesis H4 was also accepted, with a coefficient of $\beta = 0.140$ and a p-value <0.005, indicating that FC significantly influences the UI of VAs. Although FC are more commonly associated with actual usage in the original UTAUT model, recent studies have shown that they also impact intention, especially in contexts where access to technical resources and support is critical [47], [48]. In this study, the availability of connectivity, compatible devices, and digital skills positively influenced the perceived feasibility of using VAs. Kim et al. [3] highlighted that adequate infrastructure and technical knowledge are essential for encouraging the adoption of emerging technologies such as VAs. This finding empirically validates that a supportive technological environment contributes to users' willingness to adopt these tools in daily life.

B. INFLUENCE OF USAGE INTENTION ON THE USE OF VOICE ASSISTANTS

Hypothesis H5 was supported, with a coefficient of $\beta = 0.491$ and a p-value <0.001, indicating a statistically significant relationship between UI and the actual use of VAs in daily activities. This result is consistent with the UTAUT model, which posits that UI is the strongest predictor of actual usage behavior [21]. The reviewed literature reinforces this view, with numerous studies recognizing the UI as a critical stage in the technology adoption process [15]. Notably, Ghazali et al. [49] emphasized the limited number of studies focusing on the continued use of VAs despite their increasing adoption, thus confirming the relevance of this analysis. Similarly, Kim et al. [3] and Lim et al. [50] argued that investigating emerging technologies such as Vas, including Google Assistant, Siri, and Alexa, is essential for understanding how user intentions translate into actual behavior. This finding is particularly relevant in developing countries, where factors such as access, technological education, and perceived usefulness may significantly affect this relationship [16], [18]. Therefore, the model is reinforced, confirming that a strong and positive UI directly translates into greater actual use of VAs in the daily lives of users of Ecuadorian technology.

C. MODERATING EFFECT OF PRICE ON THE RELATIONSHIP BETWEEN USAGE INTENTION AND USE OF VOICE ASSISTANTS

Hypothesis H6 was supported with a coefficient of $\beta = 0.099$ and a p-value <0.005, indicating a statistically significant moderating effect of price on the relationship between UI and the actual use of VAs. This result aligns with the work of Venkatesh et al. [52], who incorporated perceived value into UTAUT2 to explain how economic factors affect the translation of intention into behavior. In this context, price should not be viewed solely as a monetary amount but rather as a user's subjective evaluation of the balance between cost and benefit [51], [53]. According to Almaiah et al. [54], when users perceive that the cost associated with using a technology is reasonable and justified by its functionality, they are more likely to confirm their initial intentions through actual use.

The theoretical literature also notes that although various studies have examined the influence of price on technology adoption [55], [56], [57], few have explored its moderating role in the UI–use relationship, especially in the case of VAs. This gap was explicitly highlighted by Kim et al. [3], who recommended that future research explore how price affects users' willingness to adopt VAs. In this context, the acceptance of H6 provides novel empirical evidence and confirms that price is a critical factor that can strengthen or weaken the transition from the intention to the actual use of VAs.

This result underscores the central role of perceived price in shaping consumer behavior toward AI-based technologies. From a statistical standpoint, the positive and significant interaction ($\beta = 0.099$, p <0.005) indicates that when users perceive voice assistants as fairly priced or offering good value for money, their UI is more likely to translate into actual behavior. Conversely, unfavorable price perceptions may dampen this relationship. Theoretically, this aligns with prior literature identifying price as both a barrier and a facilitator in technology adoption [53], [54]. While traditional UTAUT-based models often underplay the economic dimension, our findings suggest that price perception functions as a pivotal psychological filter through which intention is reinforced or weakened. Practically, this highlights the need for companies to develop pricing strategies, such as free trials, bundling, or value-added features, that enhance the perceived affordability and benefit of voice assistants. By validating the moderating effect of price, this study extends previous frameworks and provides a more context-sensitive understanding of technology acceptance in emerging markets.

VI. CONCLUSION

This study provides a comprehensive understanding of the factors influencing the UI of VAs in everyday activities as well as the role of price in this relationship. First, UI is shaped by various individual and contextual factors, including PE, EE, SI, and FC. Together, these variables significantly explain the users' predisposition to adopt VAs as functional tools in daily life. Second, the results confirmed that a high UI level directly translates into greater actual use of these devices, reinforcing the idea that internal user motivation is a key predictor of real behavior. This relationship shows that VAs are no longer perceived merely as technological innovations but rather as practical tools that enhance daily efficiency and convenience. Finally, we confirmed that price plays a moderating role in the relationship between UI and use, acting as a filter that can either strengthen or weaken this connection. In this sense, when users perceive that the benefits outweigh the costs, they are more likely to translate their intention into actual usage. Together, these findings not only extend the current knowledge on the technological acceptance of VAs but also offer practical insights for strategies aimed at increasing adoption, particularly in emerging contexts where perceived value is a determining factor.

A. IMPLICATIONS

This study has several theoretical, practical, and social implications. From a theoretical standpoint, this study extends the understanding of the UTAUT model by adapting it to the specific context of VAs and integrating price as a moderating variable, representing a significant contribution to the existing literature. By demonstrating that variables such as EE, PE, SI, and FC directly influence UI, this study reinforces the validity of the model in emerging technological environments. Furthermore, by confirming the moderating role of price between UI and actual use, this study introduces an innovative approach that addresses the gaps identified in previous research. In this way, the study not only strengthens the foundations of UTAUT, but also opens new avenues for exploring consumer behavior toward AI-powered technologies.

Practically, the findings offer valuable guidance for technology developers, software companies, and VA providers. In the Ecuadorian context, where price sensitivity and digital access remain significant barriers, companies could implement affordable pricing models such as freemium versions or educational discounts tailored to younger consumers and university populations. Marketing efforts should emphasize practical benefits and be distributed through localized digital channels (TikTok, WhatsApp groups, or university platforms). Partnerships with public and private educational institutions could serve to demonstrate the utility of voice assistants in academic and administrative tasks. Furthermore, policymakers could play a strategic role by incorporating digital literacy programs that include AI tools, such as voice assistants, into public education curricula or community training initiatives. These context-sensitive strategies not only promote adoption but also help bridge the digital divide in emerging markets like Ecuador.

From a social perspective, this study highlights the potential of VAs to simplify daily tasks, particularly among the young, urban, and educated populations. This technology not only improves individual productivity, but also contributes to bridging the digital divide by providing an intuitive and accessible form of interaction with smart devices. Additionally, by showing that perceived price influences consumer behavior, this study emphasizes the need to democratize access to these tools to ensure that the benefits of artificial intelligence are not restricted to privileged sectors. Therefore, the findings may inform public policy or digital literacy programs aimed at fostering more inclusive and equitable use of VAs in developing countries.

B. LIMITATIONS

Although the findings of this study provide significant evidence regarding UI and the actual use of VAs in daily contexts, several limitations must be considered when interpreting the results. First, it employed a cross-sectional design, which prevented the establishment of long-term causal relationships between the variables analyzed. Second, the use of non-probability sampling limits the generalizability of the findings to the broader Ecuadorian population, as the sample primarily consisted of younger university students with medium to high educational levels residing in urban areas. Additionally, the self-administered questionnaire may have introduced a response bias due to social desirability or varying levels of familiarity with VAs. Another important limitation is that the model focused exclusively on quantifiable variables, excluding qualitative aspects that could enrich the understanding of the phenomenon, such as emotions, subjective experiences, and cultural barriers to VAs use. Finally, although the study applied Harman's single factor and implemented procedural measures to ensure participant anonymity, use neutral language, and vary the item sequence to minimize bias, the use of self-reported data from a single source may introduce common method bias, which could inflate the observed relationships between variables.

C. RECOMMENDATIONS FOR FUTURE RESEARCH

Based on these limitations, several opportunities have emerged for future research. First, longitudinal studies should be conducted to observe changes in user behavior over time, particularly regarding the sustained use of VAs. Second, it would be valuable to replicate the model in other geographic regions, including rural areas and older demographic segments, to increase the external validity of the study and to explore potential cultural or generational differences. Additionally, future studies should consider complementing quantitative research with qualitative approaches, such as in-depth interviews or focus groups, to capture more subjective dimensions of user experience with VAs. Finally, future research is encouraged to adopt multi-method approaches, such as combining self-report with behavioral data or using longitudinal designs, to further validate these findings.

D. AUTHOR CONTRIBUTIONS

Each author made an equal contribution to project management, monitoring, visualization, original draft, formal analysis, research, data curation, methodology, validation. and visualization. All editors approved the manuscript after reading it.

APPENDIX A

The questionnaire used in this study comprised 26 items. Four demographic questions (gender, age, level of training, and city of residence) and 22 questions were designed to measure the variables of the hypothesized model, which were measured using a 5-point Likert scale, where 5 indicated "strongly agree" and 1 indicated "strongly disagree." Table A1 lists the questions used to measure model variables. (The questions to measure PE, EE, IS, CF, UI, and US were adapted from Kim et al. [3]. The questions used to measure PR were adapted from Lee et al. [66]. See Appendix A.

Performance Expectancy. Adapted from: Kim et al. [3]

PE1. The voice assistant is useful in my daily activities.

PE2. Using the voice assistant increases my chances of accomplishing important tasks.

PE3. Using the voice assistant helps me complete tasks faster.

PE4. Using the voice assistant increases my productivity.

Effort Expectancy. Adapted from: Kim et al. [3]

EE1. I think using a voice assistant would be easy for me.

EE2. I find interacting with the voice assistant clear and understandable.

EE3. I find the voice assistant easy to use.

Influence Social. Adapted from: Kim et al. [3]

IS1. The people who were important to me influenced me to use voice assistants.

IS2. People who influence my behavior think I should use voice assistants.

IS3. People whose opinions I value prefer to use voice assistants.

Facilitating Conditions. Adapted from: Kim et al. [3]

FC1. I believe I have the necessary skills to use a voice assistant.

FC2. I believe I have the necessary knowledge to use a voice assistant.

FC3. I believe the voice assistant is compatible with other technologies I use.

FC4. I believe I can obtain help from others when I have difficulty using a voice assistant.

Use Intention. Adapted from: Kim et al. [3]

UI1. UI1: I intend to continue using voice assistants for my daily activities.

UI2. I will try to continue using voice assistants for my daily activities.

UI3. I will use a voice assistant frequently.

Price. Adapted from Lee et al. [67]

PR1: I think voice assistants are reasonably priced.

PR2: I think voice assistants offer good value for money.

PR3: At the current price, the voice assistants provide a good value.

PR4: I think voice assistants offer good service for the price.

Use. Adapted from: Kim et al. [3]

US1. I frequently use voice assistants to carry out my daily activities.

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