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Consumer engagement with AI-powered voice assistants: A behavioral reasoning perspective

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Abstract

This study draws upon Behavioral Reasoning Theory and the Technology Acceptance Model to investigate consumer engagement with AI-powered voice assistants. The study creates a theoretical model to examine the effects of reasons for and reasons against using voice assistants. This research exemplifies attitudes towards using voice assistants and willingness to provide personal information as key constructs. The current study tests data from 491 voice assistant users via mTurk, and we utilize a multimethod analysis scheme including the partial least squares technique and the fuzzy set qualitative comparative analysis approach to provide an assessment of the proposed model. Findings indicated that while privacy cynicism has a negative impact upon the attitude towards using voice assistants, the countervailing values of trust, perceived usefulness, and ease of use have off-setting positive impact. The study also highlights the moderating role of habit on the behavioral mechanisms driving consumer engagement via willingness to provide privacy information. This research advances the emerging literature on voice assistants with respect to privacy-related factors driving consumer engagement.

KEYWORDS
artificial intelligence, behavioral reasoning theory, engagement, privacy cynicism, technology acceptance model, trust, voice assistants

1 | INTRODUCTION

Voice assistants represent a new form of voice-enabled services that simultaneously integrate elements of artificial intelligence with digital devices. Voice assistants and connected devices have become increasingly more popular with the improvement of technology and capabilities (Han & Yang, 2018; Jones, 2018). According to Statista (2022), more than four billion digital voice assistants were used globally in 2020, and 8.4 billion voice assistants are projected for 2024.

The distinction in terminology between voice assistants, chatbots, and intelligent speakers has been a source of confusion (Lister et al., 2020). Chatbots function as conversational agents within text-based interfaces, utilizing natural language processing to simulate human-like conversations (Ling et al., 2021). Intelligent speakers, on the other hand, are physical devices with built-in voice assistant capabilities, enabling control over services and devices through spoken commands. Voice assistants primarily focus on voice-based interactions, comprehending and responding to spoken commands and inquiries. While chatbots operate through text, intelligent speakers combine physical functionality with voice assistants, and voice-assistants prioritize voice interactions. These technologies enhance user experiences across different platforms and devices.

Voice assistants enable basic tasks such as calling, messaging, and seeking information (Saad et al., 2017). Voice assistants are integrated into apps for an array of functions: reading the news, online shopping, e-recommendations, and interacting with brands (McLean & Osei-Frimpong, 2019). Voice assistants represent a more natural interaction between consumers and the brand than information-retrieval and text-based reading thus motivating marketers to search for new and novel ways to increase usage of voice-enabled technologies (Mari et al., 2020). Voice assistants rely on Natural Language Processing technologies to understand consumers' voices and machine learning to improve and adapt to the commands of users (De Barcelos Silva et al., 2020). Voice assistants are designed to continuously "listen" to the users, and accordingly, are ever ready to meet users' needs (Jones, 2018). However, concerns have been expressed about how voice data are handled by voice assistants and respective managing organizations. These concerns might function as inhibitors and impede adoption and usage of voice assistants. For instance, privacy risks, privacy concerns, and general security have negative impacts on users' adoption of voice assistant according to Hoy (2018). Easwara Moorthy and Vu (2015) also found that consumers will avoid using voice assistants because of privacy concerns. Therefore, examining the factors that stimulate and/or restrain consumers' voice assistant usage is vital for marketing decision-making and strategy formulation with this emerging technology.

Despite the importance and popularity of voice assistants, scholars have focused mostly on chatbots and intelligent speakers (Jiménez et al., 2021; Lei et al., 2021; Loureiro et al., 2021). Some scholars have acknowledged that ethical aspects of Artificial Intelligence-powered (AI) technologies need further investigation (Belk et al., 2023; Dwivedi et al., 2021; Flavián & Casaló, 2021; Mariani et al., 2022). Specifically, since voice assistants represents a young and emerging market (Flavian et al., 2023), scholars have focused on drivers affecting voice assistants' usage (Aeschlimann et al., 2020; Pitardi & Marriott, 2021). For instance, Lim, Kumar, et al. (2022) found that increasing usage of voice-assistants led to more concerns about user privacy. Subsequently, privacy-related issues derived from using voice-assistants, have stimulated research on the adoption of voice assistants that focuses on barriers (Balakrishnan et al., 2021). Inhibitors/barriers such as privacy concerns, privacy cynicism, and privacy risks need continued in-depth examination and research inclusion to facilitate the development of a useful theoretical model. Balakrishnan et al. (2021) stated that technical features of voice assistants have been extensively examined in literature, but there appears to be a dearth of empirical studies that delve deeper into user attitudes.

To date, only a few studies that have investigated the fundamental reasons-for consumer engagement with voice assistants (McLean & Osei-Frimpong, 2019; Moriuchi, 2019; Prentice et al., 2023). Market predictions indicate that digital voice assistants will likely exceed 8.4 billion units by the year 2024—even greater than the global population (Laricchia, 2022). Identification and clarification of the barriers as well as enablers affecting consumer engagement with voice-assistants is ever more significant nowadays. This study examines enablers (reasons-for) and barriers (reasons-against) consumer engagement with voice-assistants; in particular, consumers attitudinal disposition towards using voice assistants and as well as willingness to provide private information are also explored.

Moriuchi (2019) found that daily shopping transactions correspond to habitual purchases that require minimal contemplation for those consumers who use voice assistants. Furthermore, Ye and Potter (2011) have shown that activities such as using a web-browser for eating, drinking, and commuting to work, has become an integral part of ordinary users' daily routines. Actions such as these are frequent and repetitive, thus providing an ideal environment for the formation of habits (Ye & Potter, 2011). Previous research also indicates that the degree of certain behaviors becomes stronger as the formation of habit becomes stronger (Hu et al., 2018). Despite these significant indicators, the moderating role of habit-formation has not been examined in the context of voice assistant. To address this gap, this study introduced "habit" as a moderator to more thoroughly comprehend the relationships between consumer attitude towards voice assistants, willingness to provide privacy information, and engagement with voice-assistants.

Theoretically, this study makes at five key contributions. First, the study clarifies the drivers of engagement with voice assistants by proposing and empirically testing a conceptual model that integrates two theories from the technology adoption and consumer behavior literature. Second, this study responds to recent calls to enable theoretical cross-fertilization in the fields of new technologies, consumer research, and marketing to advance knowledge in these areas further (Mariani et al., 2022) by integrating Behavioral Reasoning Theory (Westaby, 2005) and the Technology Acceptance Model (Davis et al., 1989) to determine the drivers of consumer engagement. In this regard, Technology Acceptance Model serves as the bedrock to test consumer use of voice assistant, while Behavioral Reasoning Theory is employed for building a comprehensive perspective of potential avoidance of using voice assistants. Third, this study provides empirical evidence of the effects of different privacy aspects, such as privacy cynicism, which have not been examined before regarding attitudes towards voice assistants, willingness to provide privacy information, and consumer engagement with this technology. Fourth, this is the first study to investigate the moderating role of habit regarding AI-powered voice assistants. Lastly, the study provides a fuzzy set qualitative comparative analysis (fsQCA) to confirm the findings extracted from the structural equation modeling.

The structure of the current paper is as follows: the theoretical framework and relevant theories follow the introduction which leads to hypotheses development. A detailed account of methodological procedures and the research design comes next and is followed by the demonstration of findings. The paper continues with a discussion of findings and implications and concludes with the limitations and suggestions for further research.

2 | THEORETICAL BACKGROUND

2.1 | Background on voice assistants

The research field of voice assistants is expanding with greater emphasis on comprehending the reasons underlying individual acceptance/usage. Previous studies examined the consequences on children resulting from their interaction with voice assistants (Aeschlimann et al., 2020), the impact of voice assistant on consumer-brand engagement (McLean et al., 2021), the effect of voice assistants on consumers' attitudes and behaviors (Poushneh, 2021), and the drivers that shape trust and attitudes towards usage intention (Pitardi & Marriott, 2021).

Furthermore, psychological and design-specific factors impact smart voice assistant usage and word-of-mouth according to Mishra et al. (2022). Also, Aw et al. (2022) investigated the effect of human-like attributes, technology attributes, and contextual factors the influence continuance usage of digital voice assistants in the shopping context. Furthermore, Maroufkhani et al. (2022) focused on the effect of brand credibility and the hedonic, utilitarian, and social presence factors on brand loyalty and continuous intention in voice assistant context. Recently, studies have examined what motivates users to adopt voice assistants for different purposes such as enhancing fashion shopping (Kautish et al., 2023), consumer–brand relationships, and consumers' well-being (Kang & Shao, 2023), the well-being and emotional connection that users have with both AI devices and their associated brands (Prentice et al., 2023), and the relationship between customer experience, satisfaction and recommendation (De Oliveira et al., 2023).

Unlike the above studies, Malodia et al. (2022) drew upon decision avoidance theory and formulated research questions seeking to demonstrate why users delay or avoid using voice assistants for transactions. Contemporarily, Jain et al. (2022) examined whether the credibility of a brand can alleviate concerns about privacy risks. Other studies have referenced users' privacy issues deriving from voice assistants (Brill et al., 2019; Hoy, 2018). Enriching and enlightening, none-the-less, the most current research on voice assistants has not investigated the "reasons-for" and "reasons-against" within a single model.

2.2 | Behavioral reasoning theory

Behavioral Reasoning Theory by Westaby (2005), provides context-specific reasons why people use and maintain certain behaviors as well as clarifies why people do or do not support them. This theory postulates that the reasons and/or motives for individuals' interlink an array of constructs in the behavioral mechanism; values and beliefs precede formation of attitudes, intentions, and behaviors and are key determinants of consumer decision-making (Gupta & Arora, 2017). These insights describe two important categories of "reasons-for" and "reasons-against" which are subjective determinants that users draw upon to support their behaviors in certain contexts (Lalicic & Weismayer, 2021).

In this regard, Behavioral Reasoning Theory provides a comprehensive understanding derived from the theory of planned behavior (Ajzen, 1991) and technology-reasoned action (Ajzen & Fishbein, 1975). The Behavioral Reasoning Theory is a recently developed marketing theory (Sahu et al., 2022) and has been utilized in different technology contexts: mobile shopping adoption (Gupta & Arora, 2017), mobile banking adoption (Gupta & Arora; Vakola, 2016), tangible product and service innovation (Claudy et al., 2015), the Internet of Things (Sivathanu, 2018), AI-enabled travel service agents (Lalicic & Weismayer, 2021). Behavioral Reasoning Theory indicates that users engage various cognitive paths and/or processes in behavioral decision-making. This theory is contextual and enables a profound understanding of determinants that occur in both the adoption or resistance of technologies (Delgosha & Hajiheydari, 2020).

Behavioral Reasoning Theory is advantageous for researchers when compared to other theories in identifying possible reasons for and/or against adoption. This theory aids in investigations of specific reasons in particular contexts while examining distinct cognitive routes in users' technology adoptions (Ryan & Casidy, 2018). Indeed, Sahu et al. (2020) advocated for further advancing Behavioral Reasoning Theory as an explanatory behavioral theory by testing it in other contexts with multiple methods and considering other moderators and mediators which could provide a more holistic perspective to customer decision processes. To this end, this study contributes to Behavioral Reasoning Theory by empirically testing in a setting where privacy plays an important role in developing positive attitudes toward engaging or declining new technologies (voice assistants). Furthermore, this study aims to assess the robustness of this theory by triangulating the results with other methods to confirm or reject its predictive power.

2.3 | Technology acceptance model

The Technology Acceptance Model (Davis et al., 1989) emphasizes two quintessential factors: the acceptance and usage of new technology (Moriuchi, 2019, 2023). This model enfolds four main constructs; context-enabled variables (perceived usefulness, perceived ease-of-use), attitude, usage intention, and usage behavior (Davis et al., 1989). With these core constructs, Technology Acceptance Model provides an explanatory capability for understanding how people accept and use new technology products and services and has been further developed and adopted to explain acceptance of continuous information and communication technologies (Pitardi & Marriott, 2021). This model has been utilized to determine the circumstances or determinants that ease technology into everyday business affairs (Moriuchi, 2019; Teo, 2016) and has been employed in different technology contexts such as virtual reality devices (Lee et al., 2019), augmented reality (Rese et al., 2017),

mobile applications (Vahdat et al., 2021), FinTech adoption (Singh et al., 2020), and e-commerce (Al-Maghrabi & Dennis, 2011).

Previous studies such as Pal et al. (2020) examined the effect of users' intention to adopt voice-enabled devices. Moriuchi (2019) also examined the two constructs derived from Technology Acceptance model to understand their impact on engagement and loyalty for voice assistants. Kowalczuk (2018) provided a theoretical model based on this model to understand the effect of enabling as well as preventing features on smart speakers' usage and adoption. A more detailed and in-depth explanation remains to investigate engagement with using voice assistants. Context-specific constructs (ease-of-use and perceived usefulness) play an important role in understanding the acceptance of specific technologies and are pivotal in this study's hypothetical model (see Figure 1).

3 │ HYPOTHESES DEVELOPMENT

3.1 │ Reasons against using voice assistants

Voice assistants inescapably introduce fundamental privacy challenges and issues that have appeared in mainstream news (Perez, 2019). Therefore, the hypothesized model in this study considers privacy-relevant factors as potential reasons-against using voice assistants. Privacy concerns is one of the negative aspects of new digital Artificial Intelligence technology and refers to users'

concerns related to personal information gathering/storing, data usage without permission, the potential misuse of private information, and/or unauthorized sharing with third parties (Choi et al., 2018; Xu et al., 2013), or concerns through data gathering, information retrieval, and/or data-mining (Vimalkumar et al., 2021). Particularly in the context of voice assistant, Easwara Moorthy and Vu (2015) found that users are not keen on using voice assistants in public settings because of privacy concerns.

In sum, users have more difficulties handling the complicated trade-offs of technology adoption with challenges of information privacy concerns. Hence, increased users' privacy concerns also impact user attitudes and behavioral intentions in various settings (Ofori et al., 2016). Additional extant literature demonstrates that privacy concerns negatively affect attitude and behavioral intention (e.g., Bailey et al., 2017; Min & Kim, 2015; Ofori et al., 2016; Schomakers et al., 2022). Therefore, the following hypothesis can be derived:

> **Hypothesis 1.** Privacy concerns have a negative influence on attitudes toward using voice assistants.

Another potential reason-against using voice assistants is privacy risk. Privacy risks refer to the perceived threat to user's privacy because of the increasing amount of information gathered without the user's awareness and subsequently losing control over one's personal information (Lee, 2009). Privacy risks are perceived as the
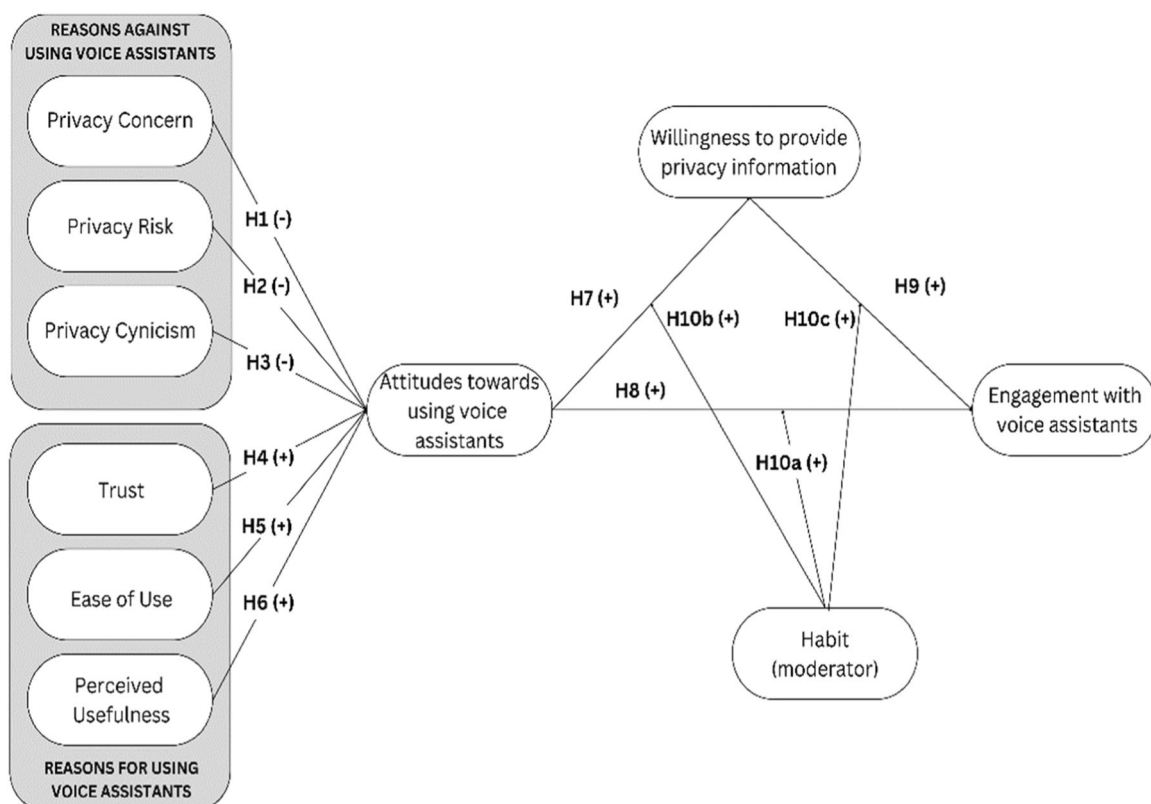

FIGURE 1 Hypothesized research model.

"expectation of losses due to the disclosure of individual information" (Xu et al., 2011, p. 804). Fortes and Rita (2016) stated that risk occurs whenever information is misused and can result from losing users' personal information in the online shopping environment. Therefore, privacy risks may hinder users from sharing their personal information and even cause them to provide inaccurate information (Abri et al., 2009) and/or cause negative attitudes towards any specific service (Walter & Abendroth, 2020). Even though privacy risks have been examined across different settings (Duan & Deng, 2022; Walter & Abendroth, 2020), the research team of Kim et al. (2019) highlighted that privacy risk varies can different outcomes. Recently, Bateman (2020) stated that voice assistant devices have enough features to create privacy risks for users. Thus:

> **Hypothesis 2.** Privacy risks have a negative influence on attitudes toward using voice assistants.

Privacy cynicism is the last factor hypothesized as a potential inhibitor of voice assistant usage. Privacy cynicism is derived from psychology and organizational literature and refers to "an attitude of uncertainty, powerlessness, and mistrust towards the handling of personal data by online services, rendering privacy protection behavior subjectively futile" (Hoffmann et al., 2016, p. 5). To manage or dispel privacy-related issues, privacy cynicism is used by consumers as a cognitive coping mechanism (Lutz et al., 2020). Cynicism emerges whenever expectations are not met in an organization (Andersson, 1996). Moreover, cynicism may diminish one's efficiency in achieving a task by decreasing one's sense of effectiveness (Schaufeli et al., 1996). Especially as highlighted by Choi et al. (2018), cynicism is related to disappointment and desperation. Hence, cynicism is considered a construct that has a negative relationship with other constructs due to corresponding negative emotions or issues (Lutz et al., 2020). In this vein, it is assumed that users who are worried about privacy issues have developed privacy cynicism as a coping mechanism. Lyu et al. (2023) recently found a significant negative effect of privacy cynicism with facial recognition services. Consequently, the following hypothesis is proposed:

> **Hypothesis 3.** Privacy cynicism has a negative influence on attitudes toward using voice assistants.

3.2 | Reasons for using voice assistants

According to Corritore et al. (2003), trust can be identified as a user's attitude of reliable expectation in response to the risk that their vulnerabilities will not be misused. Trust represents a significant foundation for building a successful interaction between the user and the agent (Moussawi & Benbunan-Fich, 2020). Trust is vital in boosting positive consumer behaviors and encouraging behaviors such as adoption and continuance intention (Hong & Cha, 2013). Hence, trust is one of the most pivotal antecedents for engaging technology (Lu et al., 2016). The literature is replete with examples of

trust as a significant determinant in different kinds of relationships in Information Systems (Foehr & Germelmann, 2020; Malodia et al., 2023). Moreover, trust is considered a positive predictor of attitude (Pitardi & Marriott, 2021). Despite the research that has focused on offline and online trust, Foehr and Germelmann (2020) stated that more research on trust between users and voice assistant is needed. Therefore, the following hypothesis is proposed:

> **Hypothesis 4.** Trust has a positive influence on attitude towards using voice assistants.

Perceived usefulness and perceived ease-of-use are additional concepts that may influence voice assistant usage. Perceived usefulness expresses how much users routinely use technologies to increase performance (Davis et al., 1989). Perceived ease-of-use refers to a user's cognitive effort necessary to understand and make use of new technology (Gefen et al., 2003). The influences of both perceived ease-of-use and perceived usefulness bear upon different outcomes such as satisfaction (Ofori et al., 2016), attitude (Bailey et al., 2017; Walter & Abendroth, 2020), intention to use and word-of-mouth intention (Cai et al., 2022) and behavioral intention (Sepasgozar et al., 2019). In the voice assistant context, Moriuchi (2019) stated that while perceived usefulness positively impacts attitudes toward voice assistants and engagement with using voice assistants, ease-of-use only affects attitudes toward voice-assistants. Recently, Choung et al. (2022) reported that users' attitude towards artificial intelligence-based voice assistant was positively impacted by perceived ease-of-use and usefulness of the technology. However, scant attention has been given to the relationship between perceived usefulness, perceived ease-of-use, and attitude toward voice assistants. Therefore:

> **Hypothesis 5.** Perceived usefulness has a positive influence on attitude towards using voice assistants.

> **Hypothesis 6.** Perceived ease-of-use has a positive influence on attitude towards using voice assistants.

3.3 | Attitude-willingness to provide privacy information and engagement with voice assistants

Attitude is a tendency to respond favorably or unfavorably towards a specific situation within a given context. One's positive or negative predisposition may decisively shape future intentions and subsequent behaviors such as loyalty, repurchase, and satisfaction. In the past two decades, researchers have investigated the effect of attitude on different outcomes such as behavioral intention in different contexts based on the Technology Acceptance Model, the Theory of Planned Behavior, and the Theory of Reasoned Action (Fortes & Rita, 2016; Venkatesh et al., 2003; Walter & Abendroth, 2020). However, the effects of attitudes toward the most recent and rapidly emerging technologies, such as voice assistants, are still largely unknown.

The focus upon "engagement" in this study examines specific interactive encounters with technology as stated by Brodie et al. (2013). Research conducted by Moriuchi (2019) stated that consumer engagement in new technology is affected by attitude, social norms, and perceived control. Therefore, this study assumes that the more positive attitude toward using voice assistants, then the more likely users will engage voice assistants. Furthermore, willingness to provide private information as a result of one's attitude towards using voice assistants is regarded as another potential key factor. Even while users benefit from voice assistants, they also have concerns related to their privacy and security issues (Hoy, 2018). However, if users hold a positive attitude towards using voice assistants, then they might be more willing to share private information. In the work of Kim and Kim (2018), Kim et al. (2019), and Trang and Weiger (2021), even though certain factors affecting willingness to provide privacy information have been examined, these scholars overlooked the effect of the attitude on willingness to provide privacy information. Thus, it is hypothesized:

> **Hypothesis 7.** Attitude toward using voice assistants have a positive influence on willingness to provide privacy information.

> **Hypothesis 8.** Attitude toward using voice assistants have a positive influence on engagement with using voice assistants.

Lastly, providing users' privacy information to voice assistants may potentially lead to higher engagement with voice assistants. Users may think they will be served better whenever sharing private information, and if so, then that may contribute to fostering higher engagement with voice assistants. Creating/cultivating higher engagement with voice-assistants may necessitate more users' privacy information to ensure more personalization and meaningful marketing strategies. Within the existing literature little attention is given to the consequences of willingness to provide privacy information. Since the effect of willingness to provide privacy information on engagement with using voice assistants has not yet fully examined, the following hypothesis is rendered:

> **Hypothesis 9.** Willingness to provide privacy information has a positive influence on engagement with using voice assistants.

3.4 | The moderating role of habit

Habit is described as the result of an automatic and unconscious response to a stimulus that generates an impulse to act (Gardner, 2015). Considering habit as a mechanism to understanding technology use has been determined to be essential (Venkatesh et al., 2003). It is believed that habits are formed the more frequently we repeat an action and then the more likely we will repeat it again (Iranmanesh et al., 2022). This is because habits are antecedents of consumers' assessments and intentions regarding technology use. Customers are satisfied with the services they habitually receive that fulfill their

needs and expectations (Amoroso & Chen, 2017). These hypotheses follow:

> **Hypothesis 10a.** Habit strengthens the relationship between attitude towards using voice assistants and engagement with using voice assistants.

> **Hypothesis 10b.** Habit strengthens the relationship between attitude towards using voice assistants and willingness to provide privacy information.

> **Hypothesis 10c.** Habit strengthens the relationship between willingness to provide privacy information and engagement with using voice assistants.

4 | METHODOLOGY

4.1 | Sampling and data collection

The sampling in this study followed a conservative approach in sample size considerations. After performing a statistical power analysis via G*Power 3.1, a minimum target of 388 survey responses was adopted (effect size = 0.5; a = 0.10; power = 0.90; df = 621; critical χ^2 = 680.08) (Faul et al., 2007). Empirical data were collected from Amazon's Mechanical Turk (mTurk) in November 2020. mTurk is a very common instrument for social and behavioral sciences for collecting high-quality and cost-effective data from a trustworthy resource (Prentice et al., 2023).

The field research study gathered data from 555 participants who have used voice assistants. Careful observation of this initial sample revealed that 26 respondents had not used voice assistants, and an additional 38 respondents failed the attention checks. After removing these responses, a final pool of 491 respondents comprised the final sample. This usable sample size is more than sufficient for data analysis because it exceeds the suggested sample size for employing the PLS technique, which is 128 in this case (a = 0.10; max number of arrows = 6) (Hair et al., 2022). Approximately 96% of the respondents who used voice assistants were from the United States. The USA sample is timely and appropriate to understand the reasoning for/against using voice assistants since Statista (2022) found that about 50% of Americans use voice assistant. Respondents included 491 users (250 males and 241 females) between 18 and 73 years of age. Individuals between 24 and 45 years old constituted the primary user group. More than 75% of the respondents have bachelor's and master's degrees. Further, respondents mostly used Google Assistant (39.3%), Alexa (26.9%), Siri (22%), and Cortana (3.7%) (Table 1).

4.2 | Construct measures

The proposed scales in the questionnaire measure perceived ease-of-use, perceived usefulness, privacy concern, privacy risk, privacy

TABLE 1 Sample demographic information.

Variable	Category	%–N (491)
Gender	Female	50.9–250
	Male	49.1–241
Age	18–24	8.6–42
	25–34	38.7–190
	35–44	26.1–128
	45–54	15.3–75
	Above 54	11.4–56
Education level	High school	24–118
	Bachelor	53.6–263
	Master's degree	17.9–88
	Doctoral Degree	1.8–9
	Professional Degree	2.6–13
Which voice assistants do you use most?	Siri	22.0–108
	Alexa	26.9–132
	Cortana	3.7–18
	Google's Assistant	39.3–193
	Missing	8.1–40

cynicism, attitude, willingness to provide privacy information, and engagement. Thirty-six items were measured on a 5-point Likert scale ranging from strongly disagree to strongly agree. A five-point Likert scale increases respondents' response rate and quality and frustration levels are reduced (Babakus & Mangold, 1992). Perceived ease-of-use and perceived usefulness were adapted from Ratten (2015) with four and five items, respectively. This study adopted a scale for privacy concerns and privacy risks based on the four items of Xu et al. (2011). We measured privacy cynicism with five items according to Choi et al. (2018), and for habit we used the three items proposed by Hsiao et al. (2016). We also measured willingness to provide private information and trust with three items from the study by Kim et al. (2019). Lastly, attitude with five items and engagement with four items were measured by borrowing from the scale of Moriuchi (2019).

4.3 | Data analysis

Partial Least Squares-based (PLS-based) Structural Equation Modeling (SEM) with SmartPLS4 software assessed the rigor of the hypothetical model. This technique was selected due to the guiding objective of data analysis, theory building and prediction, rather than confirming relationships based on a given framework (Hair et al., 2022). Given the exploratory nature of this study, both Behavioral Reasoning Theory and Technology Acceptance Model enabled the examination of the proposed hypotheses via processes

through PLS which greatly increases the explained variance of the dependent variables (Fotiadis & Stylos, 2017). Additionally, multivariate normality assumption was relaxed due to applying a data sample of more than 200 cases. In short, PLS is the most suitable technique to empirically test the novel conceptualization of user behavior within the digital voice assistant technology context.

4.4 | Common method bias (CMB)

The field study gathered data from a single source, as it relies upon self-report questionnaire forms which belong to a cross-sectional design. The CMB check is based on Harman's one-factor method for principal component factor analysis. Findings indicate the largest explained variance was 28.2%, which is less than Podsakoff et al. (2003) suggestion (50%). Therefore, CMB is not an issue. Additionally, inter-construct variance inflation factors (VIFs) has also been checked with Kock's (2015) recommendation should be less than 5; the biggest value was 3.18 and the smallest value is 1.83, so CMB is not a critical issue.

5 | RESULTS

5.1 | Measurement (outer) model evaluation

Data analysis began with assessing the measurement items which loaded between 0.747 and 0.939. The items exceeded the suggested threshold of 0.708 for factor loadings (Hair et al., 2019, 2022). The average variance extracted (AVE) ranged from 0.622 to 0.774, which was above the value of 0.5 for all constructs (Hair et al., 2022) which shows acceptable convergent validity. The internal consistency of the scales demonstrated composite reliability (CR) ranging from 0.865 to 0.915, and Cronbach's α varying from 0.786 to 0.877, again which are higher than the minimum value of at least 0.70. In-toto, this indicates internal consistency and reliability criteria are met for all constructs (see Supporting Information: Appendix A).

Next, discriminant validity was measured per Fornell and Larcker (1981). The AVE values the constructs found to be bigger than any of the cross-loadings with other factors (see Supporting Information: Appendix B). Furthermore, discriminate validity was checked by using Heterotrait-Monotrait (HTMT) ratio (see Supporting Information: Appendix C), and were met according to Henseler's et al. (2015) proposed values being less than 0.85 or 0.90. Overall, discriminant validity was well-established for the factorial structure.

5.2 | Structural (inner) model evaluation

The results of a bootstrapping test with 10,000 subsample and one-tailed test according to Hair et al. (2022) appear in Table 2. Path coefficients showed the relationship strength between dependent and independent constructs. It appears that privacy concern

TABLE 2 Hypotheses results.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T Statistics (|O/STDEV|)	p Values
H1: Privacy Concern -> Attitude towards using voice assistant	0.151	0.141	0.051	2.960	0.002***
H2: Privacy Risk -> Attitude towards using voice assistant	−0.064	−0.056	0.050	1.285	0.099*
H3: Privacy Cynicism -> Attitude towards using voice assistant	−0.132	−0.125	0.059	2.243	0.012**
H4: Trust -> Attitude towards using voice assistant	0.140	0.134	0.052	2.712	0.003***
H5: Ease-of-use -> Attitude towards using voice assistant	0.386	0.391	0.047	8.210	0.000***
H6: Perceived usefulness -> Attitude towards using voice assistant	0.414	0.416	0.057	7.331	0.000***
H7: Attitude towards using voice assistant -> Willingness to provide privacy information	0.288	0.286	0.047	6.147	0.000***
H8: Attitude towards using voice assistant > Engagement with using voice assistant	0.258	0.255	0.039	6.553	0.000***
H9: Willingness to provide privacy information -> Engagement with using voice-assistant	0.292	0.293	0.049	5.991	0.000***
H10a: Habit*Attitude towards using voice assistants -> Engagement with using voice-assistant	−0.003	−0.004	0.035	0.085	0.466
H10b: Habit*Attitude towards using voice assistants -> Willingness to provide privacy information	0.138	0.136	0.039	3.526	0.000***
H10c: Habit* Willingness to provide privacy information > Engagement with using voice assistant	0.060	0.060	0.037	1.645	0.050**
Specific indirect effect Attitude > Willingness to provide privacy information > Engagement with using voice assistant	0.084	0.084	0.022	3.761	0.000***

Note: PLS results of the research model (*p < 0.10, **p < 0.05, and ***p < 0.01, one-tailed).

Abbreviation: PLS, Partial Least Squares.

surprisingly had a significant and positive influence on attitude towards using voice assistants (β = 0.151, T = 2.952), hence H1 was rejected. Moreover, the negative relationship between privacy risk and attitude toward using voice assistants (β = −0.064, T = 1.285) was statistically significant. Therefore, H2 was supported. Privacy cynicism (β = −0.132, T = 2.243) has a negative impact on attitudes towards using voice assistants, hence H3 hypothesis was supported. Regarding reasons for using voice assistants, trust (β = 0.140, T = 2.712), ease-of-use (β = 0.386, T = 8.210) and perceived usefulness (β = 0.414, T = 7.331) exhibit significant and positive impacts on attitude towards using voice assistants. Therefore, support is demonstrated for H4, H5, and H6, respectively. Additionally, attitude towards using voice assistants has a positive impact on willingness to provide personal information and engagement with using voice assistants, respectively based on H7 (β = 0.288, T = 6.147), and H8

(β = 0.258, T = 6.553). Further, the effect of willingness to provide privacy information on engagement with using voice assistants was significantly positive, so H9 (β = 0.292, T = 5.991) was supported.

Lastly, we examine the moderating role of habit on the relationship between attitude towards using voice assistants and engagement with using voice assistants was examine in light of H10a (β = −0.003, T = 0.085); also, attitude towards using voice assistants and willingness to provide privacy information H10b (β = 0.138, T = 3.526); and, willingness to provide privacy information and engagement with using voice assistants H10c (β = 0.060, T = 1.645). The moderator role of habit in H10b and in H10c was confirmed, however, habit did not show a moderation role in H11a. Finally, our analysis reveals that willingness to provide privacy information positively mediates the relationship between attitude towards using voice assistants and engagement with using voice assistants

($β$ = 0.084, T = 3.761). In summation, all structural (inner) model hypotheses outcomes and standard regressions weights are depicted in Figure 2.

5.3 | The fsQCA model

Considering the PLS findings, this study reexamined the role of attitude towards using voice assistants and engagement with using voice assistants through fsQCA to provide a more holistic and comprehensive understanding of its outcomes and consequences. The purpose of fsQCA is to evaluate the multiple complex antecedent conditions (or causal recipes) that lead to high membership in the two outcome conditions, which are attitude toward using voice assistants and engagement with using voice assistants.

FsQCA is a hybrid approach that includes qualitative-quantitative features to explore various cases that demonstrate phenomenon in complicated conditions (Ragin, 2009). This approach strengthens the results of theoretical models initially investigated with SEM (Bawack et al., 2021) by increasing the understanding of the mechanisms behind the users' perceptions of voice assistants' engagement which were not clarified through PLS-SEM.

fsQCA is created through a calibration process of interval scale variables to identify set configurations. The calibration yields scores that vary from 0 (*not a member*) to 1 (*full member*), with 0.5 denoting the highest vagueness in membership (Ragin, 2009). Summated measures are calculated to calibrate the variables by summing items measuring each construct according to breakpoints 0.95, 0.50, and 0.05, respectively (Ragin et al., 2008).

Then, the findings of fsQCA analysis are arrayed in a truth table forged via an algorithmic two-phase rational procedure. The first phase creates a truth-table spreadsheet from the main data to determine the causal and outcome conditions to integrate into the analysis (Valaei et al., 2017). Due to the large number of samples in this study (n > 100), only configurations with a minimum frequency of three were analyzed (Bawack et al., 2021). Configurations fixed in this analysis (consistency) encompassed at least 80% of the cases, denoting the extent to which a causal solution leads to the outcome (in this study, engagement) (Ragin et al., 2008).

Two models were formed to express attitude towards using voice assistants and another model to render consumer engagement with using voice assistants, thus providing different solutions. The presence of a condition is typically exhibited with (●), the absence/negation with a crossed-out circle (⊗), and the "do not care" condition with a space (Bawack et al., 2021; Fiss, 2011; Pappas & Woodside, 2021).

The first outcome condition in Table 3 shows that six possible pathways lead to attitude towards using voice assistants. The findings illustrate an overall solution coverage as 0.851 and consistency as 0.932. Solution 1 set with the highest consistency (0.994) and satisfactory coverage (0.489), revealed that the high presence of all antecedents is a necessary condition for the development of attitude toward using voice assistants. Solution 2 set covering highest (0.951) and coverage (0.826) demonstrated that the presence of perceived usefulness and the absence of privacy cynicism, privacy risk, and ease-of-use would lead to attitude toward using voice-assistants. Solution 3 set having the highest (0.950) and coverage (0.824) indicated the presence of perceived usefulness and the absence of
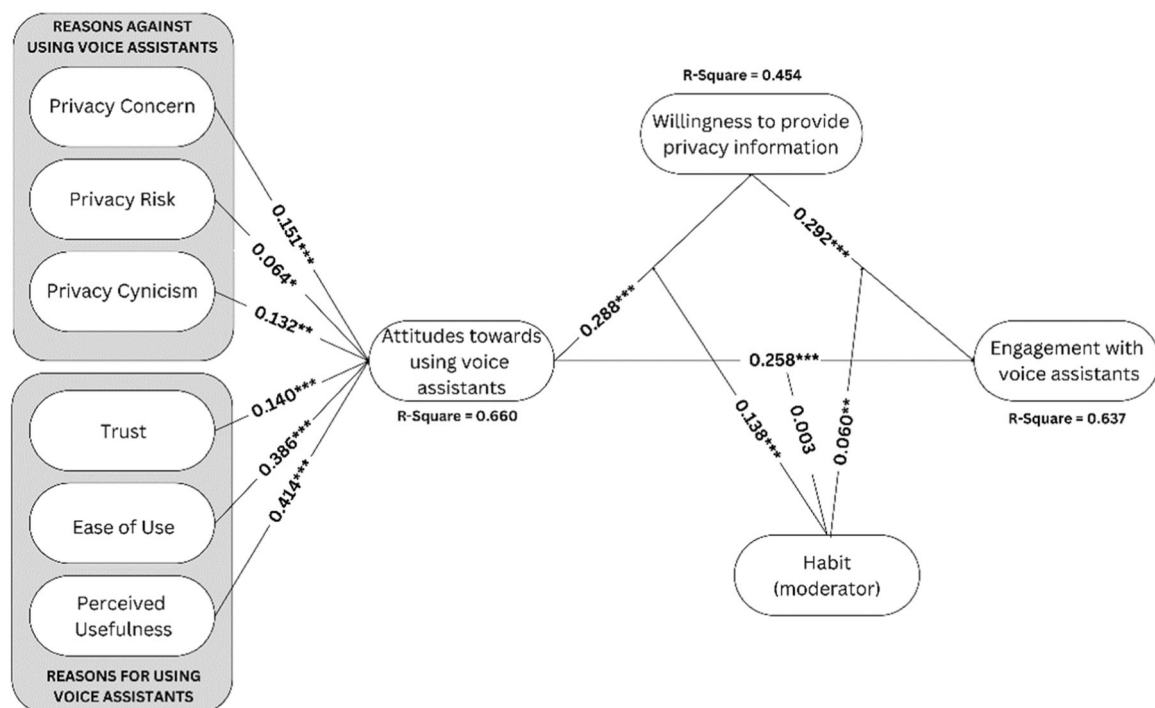

FIGURE 2 Validated research model.

TABLE 3 fsQCA Findings.

Model: Attitude = f (privacy cynicism, privacy risk, privacy concern, trust, perceived usefulness, ease-of-use)						
	Solution					
Configuration	1	2	3	4	5	6
Reasons against						
Privacy cynicism	●	○	○	○	○	○
Privacy concern	●			○	○	●
Privacy risk	●	○		○	○	
Reasons for						
Ease-of-use	●	○	○	●	○	○
Perceived usefulness	●	●	●	○		
Trust	●		○	○	●	○
Consistency	0.994	0.951	0.950	0.951	0.960	0.873
Row coverage	0.489	0.826	0.824	0.788	0.670	0.777
Unique coverage	0.007	0.002	0.002	0.008	0.005	0.034
Overall solution consistency	0.932					
Overall solution coverage	0.851					

Note: Blank, not considered in the solution; hollow circles, absence of the variable; The black circles, presence of the variable.

privacy cynicism, ease-of-use, and that trust would result in attitude towards using voice-assistants. Solution 4 set has substantial consistency (0.951) and important coverage (0.788) which highlights the presence of ease-of-use; the absence of the other antecedents are key conditions that lead to attitude towards using voice-assistants. Solution 5 includes high consistency (0.960) and sufficient coverage (0.670) which show the presence of trust and the absence of reasons against factors; ease-of-use would constitute attitude towards using voice assistants. Lastly, Solution 6 set with satisfactory consistency (0.873) and coverage (0.77) denotes the presence of privacy concerns and the absence of privacy cynicism; trust would result in an attitude toward using voice assistants.

The second outcome shown in Table 4 highlights the coverage and the consistency of the eight combinations that adequately demonstrate high engagement with using voice-assistants. These findings demonstrate an overall solution coverage of 0.734 and consistency of 0.946, which underscore the importance of empirical and theoretical importance based on the findings (Paykani et al., 2018). Solution 1 highlights the combination of high consistency (0.973) with notable coverage (0.608), hence providing the best explanation for engagement with using voice assistants and illustrates that each presence of the antecedents is an essential condition for engagement with using voice assistants. Solution 2 with an

acceptable high consistency (0.805) and significant coverage (0.742), indicates the presence of privacy concerns, privacy risks, attitudes towards using voice assistants, and the absence of the other antecedents would entice engagement with using voice assistants. Solution 3 presents substantial consistency (0.797) and coverage (0.884), and this condition illustrates that the presence of perceived usefulness and the absence of privacy cynicism, privacy concern, privacy risk, ease-of-use, and willingness to provide privacy information would lead to more engage with using voice assistants. Solution 4 has important consistency (0.819) and coverage (0.872). The similarities of Solution set (4) and Solution 3 set denote the presence of perceived usefulness and attitude together, and the absence of privacy cynicism, privacy concern, ease-of-use, and willingness to provide privacy information that would lead to engagement with using voice assistants. Solution 5 demonstrates important consistency (0.815) and high coverage (0.847). Solution 5 highlights the presence of ease-of-use and attitude, and the absence of the rest antecedents is conducive to engagement with using voice assistants. Solution 6 is notably different and shows high consistency (0.890) and importance coverage (0.787); the presence of a willingness to provide privacy information and the absence of the rest antecedents facilitate engagement with using voice assistants. Solution 7 includes important consistency (0.895) and substantial coverage (0.800), pointing out that the presence of trust and the absence of the rest antecedents lead to engagement with using voice assistants.

Lastly, Solution 8 is also remarkably consistent (0.922) and has substantial coverage (0.782). This solution set proposes that the presence of perceived usefulness, attitude, willingness to provide privacy information and the absence of privacy-related factors and ease-of-use provide engagement with using voice assistants.

6 | DISCUSSION, CONCLUSIONS, AND FUTURE RESEARCH

As stated by Flavian et al. (2023), voice assistants still represent a young market, and voice-enabled technologies are becoming more widely adopted. Considering the increase in the usage of voice assistants in people's daily lives, this study focused on the effect of the reasons for using voice assistants and the reasons against not using voice assistants upon engagement with using voice assistants through both attitudes towards using voice assistants as well as willingness to provide privacy information. Drawing on the Behavioral Reasoning Theory and Technology Acceptance Model, we formulated hypotheses related to the reasons against using voice assistants, including privacy concerns, privacy risk, and privacy cynicism, and the reasons for using voice assistants covering trust, perceived usefulness, and ease-of-use have an influence in attitude towards using voice assistants, and consequently influencing willingness to provide privacy information and engagement with using voice assistants. Moreover, we also examine the role of habit in the voice assistant context.

TABLE 4 fsQCA findings.

Model: Engagement = f (privacy cynicism, privacy risk, privacy concern, trust, attitude, willingness to provide privacy information, perceived usefulness, ease-of-use)								
	Solution							
Configuration	1	2	3	4	5	6	7	8
Reasons-against								
Privacy cynicism	○	○	○	○	○	○	○	○
Privacy concern	●	●	○	○	○	○	○	○
Privacy risk	●	●	○		○	○	○	○
Reasons-for								
Ease-of-use	●	○	○	○	●	○	○	○
Perceived usefulness	●	○	●	●	○	○	○	●
Trust	●	○	○	○	○	○	●	
Attitude towards using voice assistants	●	●		●	●	○	○	●
Willingness to provide privacy information	●	○	○	○	○	●	○	●
Consistency	0.973	0.805	0.79	0.819	0.815	0.890	0.890	0.922
Row coverage	0.608	0.742	0.884	0.872	0.847	0.787	0.800	0.782
Unique coverage	0.009	0.002	0.003	0.002	0.001	0.004	0.005	0.014
Overall solution consistency	0.946							
Overall solution coverage	0.734							

Note: blank, not considered in the solution; hollow circles, absence of the variable; The black circles, presence of the variable.

First, this study found that privacy concern positively affects attitude toward using voice assistants. Some fsQCA findings have stated that the presence of privacy concerns is essential for shaping attitudes toward using voice assistants. Specifically, two out of six solutions indicated that privacy issues play a significant role in shaping relevant attitudes in using voice assistants. In the strongest solution, which involves all constructs proposed in the hypothetical model, all three privacy items (cynicism, concern, risk) are activated. This finding is consistent with Shin's study (2010). However, this finding is still not entirely congruent with previous studies showing the negative relationship between privacy concerns and attitudes toward using voice assistants (Pitardi & Marriott, 2021). The reason is that the escalation of privacy concerns among individuals triggers a heightened level of scrutiny regarding the handling, storage, and utilization of their personal data. This increased awareness prompts users to actively assess the extent to which voice assistants provide privacy protection. Particularly, when users have increased privacy concerns, then this leads to greater awareness, empowers them to exert control over their personal information, and stimulates the demand for features that enhance privacy. Consequently, users may develop a more positive attitude toward using voice assistants. Simultaneously, managers could leverage privacy as a competitive advantage, creating a conducive environment that encourages users to engage with voice-assistants. Furthermore, even though

Vijayasarathy (2004) found a nonsignificant relationship between privacy concern and attitude, he hypothesized that privacy would positively affect attitude in online shopping. Another alternative explanation is that users already know that new technology has many privacy issues. Therefore, privacy concerns may not be perceived as a factor affecting attitude towards using voice assistants. On the contrary, it may be assumed that voice assistants are securely based on privacy issues and privacy concern is essential to shape a favorable attitude towards using voice assistants.

Second, the negative effect of privacy risk on attitude towards using voice assistants is significant. This finding is consistent with the existing literature (Duan & Deng, 2022; Fortes & Rita, 2016; Walter & Abendroth, 2020), but it is not consistent with Vimalkumar et al.'s study (2021) who found that privacy risk does not have any impact on users' adoption behaviors in voice assistant context. Similarly, the fsQCA findings showed that only the presence of privacy risk is insufficient to lead to an attitude toward using voice assistants. One possible explanation for this finding could be that users do not perceive any risks associated with voice assistants if they do not use them for risky tasks (Pitardi & Marriott, 2021). Since privacy risk has been newly examined in the context of voice assistants, the relationship between privacy risk and attitude toward using voice assistants needs more investigation. Another notable contribution is as per the relevant hypothesis, was the negative effect of privacy

cynicism on attitude toward using voice assistants; this finding builds on previous studies (Acikgoz & Vega, 2022) and offers new insights in this area.

Furthermore, we found that trust positively impacts attitudes toward using voice-assistants. Pitardi and Marriott's lone study (2021) investigated the relationship between trust and attitude toward using voice assistants in an integrated manner. Even though trust has been examined in different contexts for analyzing the efficiency of voice assistants (Loureiro et al., 2021), some scholars (McLean et al., 2021) state that trust in voice assistants remains an issue despite making the users' life much easier.

Perceived usefulness and ease-of-use also influence positive attitudes toward using voice assistants. The results of this study have been confirmed in other technology-based contexts (Bailey et al., 2017; Walter & Abendroth, 2020). The findings in this study's voice assistant context concur with Moriuchi (2019) regarding the effect of perceived usefulness on attitude toward using voice-assistants. Moreover, Pitardi and Marriott's study (2021) also validate the findings herein showing the positive effect of perceived usefulness and ease-of-use on attitude towards using voice assistants. Additionally, Kang and Namkung (2018) also demonstrated that perceived usefulness is a more effective determinant factor than ease-of-use for specifying users' attitudes toward any technology.

This study examined the effect of attitude towards using voice assistants on willingness to provide personal information and the findings demonstrate that users with a favorable attitude toward using voice assistants are more willing to share their personal information. Even though Kim et al. (2019) identified factors influencing the willingness to provide privacy information, they did not include the effect of attitude on willingness to provide personal information. Shortly thereafter, Cao and Wang (2022) called for research investigating other potential drivers (except privacy concerns) that could impact information disclosure but excluded privacy concerns. However, both attitudes towards using voice assistants and willingness to provide personal information were examined in this study and found to have a significant positive effect on engagement with using voice assistants. This study explored factors that affect engagement with using voice assistants and answered the demand for integrating technologies with marketing as stated by Moriuchi (2019). The findings of this study show that willingness to provide privacy information positively mediates the relationship between attitude towards using voice assistants and engagement with using voice assistants.

Lastly, habit as a moderator plays an important role in the relationship between attitude towards using voice assistants and willingness to provide privacy information and willingness to provide privacy information and engagement with using voice assistants. The fsQCA solutions on engagement have also shown that privacy concern and privacy risk contribute to the best two solutions. Overall, the other six solutions which did not include the privacy factor in their proposed solution demonstrated a much lower consistency in their proposed structure Privacy is key to decision-making modelling of consumer behavioral mechanism with respect to engaging with voice assistants.

6.1 | Theoretical implications

This research study makes several theoretical contributions. First, by integrating technology adoption and consumer behavior theories, researchers can holistically examine the drivers behind engagement that go beyond enablers but also consider potential barriers around privacy dimensions. While some driving factors have been explored in previous research studies, privacy dimensions have not been sufficiently examined empirically though these are important for this type of technology. Although research on voice assistants has gained increasing attention, there has been limited investigation from a privacy-related perspective. Thus, this study responds to Mehta's (2022) call for research on investigating the relationship between the use of AI-technology and users' privacy-related concerns. Moreover, Dwivedi et al. (2021) emphasized the necessity for research on the ethics AI technology related to privacy and security from both internal (user) and external (manager) stakeholders' perspectives. Hence, this study contributes to understanding the factors of "reasons against" using voice assistants. However, although Balakrishnan et al. (2021) have investigated enablers and inhibitors to resistance toward adopting AI-powered voice assistants, this study adopted a different perspective by adding privacy-related constructs along with perceived ease-of-use and perceived usefulness. This study's theoretical model explains actual behavior, setting it apart from most studies in the extant literature.

This empirical study also provides a unique inclusion by testing privacy cynicism. Even though cynicism has been well-developed in management and organization literature, Lutz et al. (2020) maintain that privacy cynicism needs even more conceptual work. Acikgoz and Vega (2022) also called for research on privacy cynicism in AI-powered technologies because privacy cynicism might provide a fuller explanation for the incongruence between users' privacy attitudes and their privacy behaviors (Van Ooijen et al., 2022). This study investigated the effect of privacy cynicism in the voice assistant context.

Another theoretical implication of this study refers to the effect of trust upon voice-assistant usage (Foehr & Germelmann, 2020; Pitardi & Marriott, 2021). Nonetheless, Pitardi and Marriott (2021) endeavor to understand what leads users to trust voice assistants. Although trust has been extensively examined in AI-powered contexts, this holds true mostly for the chatbot contexts (Lei et al., 2021; Loureiro et al., 2021; Mostafa & Kasamani, 2022). This study examined the effect of users' trust on attitudes toward voice assistants and substantially contributed to examining the role of trust in voice assistant context.

Furthermore, the relationships between attitude towards using voice assistants, willingness to provide personal information, and engagement with using voice assistants have not been previously examined. This study sheds light on user engagement with using voice assistants as influenced by consumers' attitudes towards using voice assistants and their willingness to provide privacy information. Also, habit as a moderator has not been examined in the voice assistant context. Voice assistants are considered daily usage devices

for many consumers. The rate of voice assistants for everyday usage has witnessed a dramatic uptick during the recent Covid-19 pandemic such that these devices are among users' daily habits. Hence, examining the role of habit in the context of voice assistant also makes a substantive contribution to the existing literature.

6.2 | Managerial implications

The findings of this study indicate a significant linkage between privacy-related factors and attitude toward using voice-assistants which leads to the willingness to provide privacy information and engagement with using voice-assistants. Marketing practitioners and managers of voice-assistant brands can strategize and formulate marketing promotions or organizational offerings built on privacy-related determinants. Furthermore, voice assistant managers who pay attention to these factors and develop user experiences related to voice assistants, accordingly, stand to or enhance customer-based brand equity (brand awareness, brand association, brand love).

Managers can leverage privacy concerns as a competitive advantage by emphasizing that voice assistants provide high-level privacy protection to create a positive attitude towards using voice assistants. To build on privacy-related determinants in voice assistant experiences, managers can enhance privacy policies, implement privacy-enhancing features, educate users about specific privacy measures, incorporate privacy messaging in marketing, ensure compliance with privacy regulations, and engage with users for feedback. This way, privacy concerns would be converted to a reason for using voice-assistants instead of a reason against using voice assistants. Voice assistant brands, companies, and managers would be wise to focus on the users' improving privacy cynicism for voice assistants. Privacy cynicism to cope with privacy concerns is legitimate and needs to be included in business decisions and interfacing with users of voice assistants.

Since a significant negative relationship between privacy risk and attitude toward using voice assistants was supported by the data analysis, managers and companies should ensure that voice assistants do not create privacy risks. Privacy risks might generate severe concerns to users, and restraints may be felt in using voice assistants (McLean & Osei-Frimpong, 2019). To mitigate privacy risks associated with voice assistants, managers should prioritize data security measures, adopt privacy by design principles, practice data minimization, ensure transparency and obtain user consent, provide user control over privacy settings, conduct regular privacy audits, and promote privacy training and awareness. These actions aim to instill user confidence, address privacy concerns, and foster a trustworthy environment, ultimately leading to increased user adoption and satisfaction with voice assistant technology.

In addition to the motives for utilizing voice assistants, managers ought to devise tactics that enhance trust, perceived ease-of-use, and perceived usefulness. To achieve this, managers can employ strategies such as transparent communication, user-friendly design, personalization and customization options, reliable and accurate responses, proactive assistance, and continuous improvement. By focusing on these areas, managers can improve the overall user experience, increase user satisfaction, and maximize the value derived from voice assistants' technology.

The findings illustrate that trust is less impactful on attitude towards using voice assistants when compared to other explanations; hence building trust for users in their voice assistants experience should be addressed. Another way is to derive benefit is from credible and expert influencers who might inspire their followers by promote voice assistants. Lastly, managers can share the benefits that users derive from utilizing these technologies.

Managers should be aware that positive attitudes towards using voice assistants cause willingness to provide personal information and increase engagement with using voice assistants. Providing personal information may be important for managers to create user personalization to provide a better experience for voice assistant users. The managers can provide incentives (advanced search capabilities or providing a smart working environment) for their users when they share their privacy information. The attractive aspect of such offers can strengthen users' inclination to reveal information.

6.3 | Limitations and suggestions for future research

This research study only examines the effects of reasons-for using voice-assistants and reasons-against using voice-assistants on engagement with using voice-assistants. Future research may look at the different outcomes, such as continuance intention of using voice-assistants, or electronic word-of-mouth (e-wom) intention, and others as indicated in Table 5. In this research, Technology Acceptance Model and Behavioral Reasoning Theory are combined, but future research may focus more on the second one by using other theories to delve into the reasons-for using voice-assistants and reasons-against using voice-assistants with different antecedents. For example, future research may develop a different perspective by employing the Privacy Calculus Theory combined with Protection Motivation Theory, which may be alternatively utilized in understanding privacy issues that new technology devices create. Specifically, privacy cynicism requires more research in this context. Future research may consider the effect of privacy cynicism on or through different constructs as mentioned above by employing different mediators, such as commitment (Hernandez-Ortega & Ferreira, 2021).

Another pivotal point is that this study conducts a survey that relies on self-reported measures in terms of ownership and the habitual usage of voice-assistant devices, and the quantitative data collected to evaluate the research model. Although this is not a limitation perse, future research might combine semi-structured interviews or in-depth interview data to understand the voice assistant context more fully as well as include other methods to measure actual behavior. Another suggestion is to aim for a continuous observation of the consumer engagement of using

TABLE 5 Suggestions and research questions for future studies.

Suggested variables, theories, and techniques for future research
Variables; Continuance intention of using digital technology (Yan et al. (2021); electronic word-of-mouth (e-wom) intention (Wandoko & Panggati (2022); commitment (Hernandez-Ortega & Ferreira, 2021)
Theories; Privacy Calculus Theory (Awad & Krishnan, 2006); Protection Motivation Theory (Rogers, 1975); Communication Privacy Management Theory (Petronio & Caughlin, 2006)
Techniques; In-depth interviews or/and online focus groups (Stylos et al. (2021); continuous observation of consumers' engagement (Blut et al. (2023); experimental design (Whang & Im, 2021); longitudinal schemes (Lim, Rasul, et al., 2022)
Some example research questions for future research
RQ1: How do the reasons that users have for using or not using voice assistants impact their intention to share their experiences through electronic word-of-mouth (e-WOM)? What are the underlying factors that drive this relationship and shape their decision to spread the word about their voice assistant experiences?
RQ2: How can we combine theories like the Privacy Calculus Theory and Protection Motivation Theory with Behavioral Reasoning Theory to gain a deeper understanding of why users choose to use or avoid using voice assistants?
RQ3: How does commitment come into play as a mediator in this relationship, influencing the level of engagement and the decisions individuals make regarding their privacy concerns?
RQ4: How can qualitative methods like semi-structured interviews or in-depth interviews provide a more comprehensive understanding of how users interact with voice assistants and the contextual factors that shape their behavior?
RQ5: What are the specific challenges and opportunities faced by different industries, such as retailing, tourism, or hospitality, in effectively engaging consumers through voice assistants?

voice-assistants since usage is an on-going behavior and this would fit with longitudinal research schemes. Lastly, future studies may investigate participants' inclination to use voice-assistants focusing on a specific service industry such as retailing, tourism, and hospitality (buying tickets) or other service contexts.

CONFLICT OF INTEREST STATEMENT
The authors declare no conflict of interest.

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

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REFERENCES

Abri, D. A., McGill, T., & Dixon, M. (2009). Examining the impact of E-privacy risk concerns on citizens' intentions to use E-government services: An Oman perspective. *Journal of Information Privacy and Security*, 5(2), 3–26.

Acikgoz, F., & Vega, R. P. (2022). The role of privacy cynicism in consumer habits with voice-assistants: A technology acceptance model perspective. *International Journal of Human–Computer Interaction*, 38, 1138–1152.

Aeschlimann, S., Bleiker, M., Wechner, M., & Gampe, A. (2020). Communicative and social consequences of interactions with voice-assistants. *Computers in Human Behavior*, 112, 106466.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211.

Ajzen, I., & Fishbein, M. (1975). A Bayesian analysis of attribution processes. *Psychological Bulletin*, 82(2), 261–277.

Al-Maghrabi, T., & Dennis, C. (2011). What drives consumers' continuance intention to e-shopping? Conceptual framework and managerial implications in the case of Saudi Arabia. *International Journal of Retail & Distribution Management*, 39(12), 899–926.

Amoroso, D. L., & Chen, Y. A. N. (2017). Constructs Affecting Continuance intention in consumers with mobile financial apps: A dual factor approach. *Journal of Information Technology Management*, 28(3), 1–24.

Andersson, L. M. (1996). Employee cynicism: An examination using a contract violation framework. *Human Relations*, 49, 1395–1418.

Aw, E. C. X., Tan, G. W. H., Cham, T. H., Raman, R., & Ooi, K. B. (2022). Alexa, what's on my shopping list? Transforming customer experience with digital voice-assistants. *Technological Forecasting and Social Change*, 180, 121711.

Awad, N. F., & Krishnan, M. S. (2006). The personalization privacy paradox: An empirical evaluation of information transparency and the willingness to be profiled online for personalization. *MIS Quarterly*, 30, 13–28.

Babakus, E., & Mangold, W. G. (1992). Adapting the SERVQUAL scale to hospital services: An empirical investigation. *Health Services Research*, 26(6), 767–786.

Bailey, A. A., Pentina, I., Mishra, A. S., & Ben Mimoun, M. S. (2017). Mobile payments adoption by US consumers: An extended TAM. *International Journal of Retail & Distribution Management*, 45(6), 626–640.

Balakrishnan, J., Dwivedi, Y. K., Hughes, L., & Boy, F. (2021). Enablers and Inhibitors of AI-Powered Voice Assistants: A Dual-Factor Approach by Integrating the Status Quo Bias and Technology Acceptance Model. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-021-10203-y

Bawack, R. E., Wamba, S. F., & Carillo, K. D. A. (2021). Exploring the role of personality, trust, and privacy in customer experience performance during voice shopping: Evidence from SEM and fuzzy set qualitative comparative analysis. *International Journal of Information Management*, 58, 102309. https://doi.org/10.1016/j.ijinfomgt.2021.102309

Belk, R. W., Belanche, D., & Flavián, C. (2023). Key concepts in artificial intelligence and technologies 4.0 in services. *Service Business*, 17(1), 1–9.

Blut, M., Kulikovskaja, V., Hubert, M., Brock, C., & Grewal, D. (2023). Effectiveness of engagement initiatives across engagement platforms: A meta-analysis. *Journal of the Academy of Marketing Science*, 1–25.

Brill, T. M., Munoz, L., & Miller, R. J. (2019). Siri, Alexa, and other digital assistants: a study of customer satisfaction with artificial intelligence applications. *Journal of Marketing Management*, 35(15–16), 1401–1436.

Cai, R., Cain, L. N., & Jeon, H. (2022). Customers' perceptions of hotel AI-enabled voice-assistants: Does brand matter? *International Journal of Contemporary Hospitality Management*, 34(8), 2807–2831.

Cao, G., & Wang, P. (2022). Revealing or concealing: Privacy information disclosure in intelligent voice-assistant usage-a configurational approach. *Industrial Management & Data Systems*, *122*(5), 1215–1245.

Choi, H., Park, J., & Jung, Y. (2018). The role of privacy fatigue in online privacy behavior. *Computers in Human Behavior*, *81*, 42–51.

Choung, H., David, P., & Ross, A. (2022). Trust in AI and Its Role in the Acceptance of AI Technologies. *International Journal of Human–Computer Interaction*, *39*(9), 1727–1739. https://doi.org/10.1080/10447318.2022.2050543

Claudy, M. C., Garcia, R., & O'Driscoll, A. (2015). Consumer resistance to innovation—A behavioral reasoning perspective. *Journal of the Academy of Marketing Science*, *43*(4), 528–544.

Corritore, C. L., Kracher, B., & Wiedenbeck, S. (2003). Online trust: Concepts, evolving themes, a model. *International Journal of Human-Computer Studies*, *58*(6), 737–758.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*, 982–1003.

de Barcelos Silva, A., Gomes, M. M., da Costa, C. A., da Rosa Righi, R., Barbosa, J. L. V., Pessin, G., De Doncker, G., & Federizzi, G. (2020). Intelligent personal assistants: A systematic literature review. *Expert Systems with Applications*, *147*, 113193. https://doi.org/10.1016/j.eswa.2020.113193

Delgosha, M. S., & Hajiheydari, N. (2020). On-demand service platforms pro/anti adoption cognition: Examining the context-specific reasons. *Journal of Business Research*, *121*, 180–194.

Duan, S. X., & Deng, H. (2022). Exploring privacy paradox in contact tracing apps adoption. *Internet Research*, *32*(5), 1725–1750.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., ... Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice, and policy. *International Journal of Information Management*, *57*, 101994.

Easwara Moorthy, A., & Vu, K. P. L. (2015). Privacy concerns for use of voice activated personal assistant in the public space. *International Journal of Human-Computer Interaction*, *31*(4), 307–335.

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G* Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior research methods*, *39*(2), 175–191.

Fiss, P. C. (2011). Building better causal theories: A fuzzy set approach to typologies in organization research. *Academy of management journal*, *54*(2), 393–420.

Flavián, C., Akdim, K., & Casaló, L. V. (2023). Effects of voice-assistant recommendations on consumer behavior. *Psychology & Marketing*, *40*, 328–346.

Flavián, C., & Casaló, L. V. (2021). Artificial intelligence in services: Current trends, benefits, and challenges. *The Service Industries Journal*, *41*(13–14), 853–859.

Foehr, J., & Germelmann, C. C. (2020). Alexa, can I trust you? Exploring consumer paths to trust in smart voice-interaction technologies. *Journal of the Association for Consumer Research*, *5*(2), 181–205.

Fortes, N., & Rita, P. (2016). Privacy concerns and online purchasing behaviour: Towards an integrated model. *European Research on Management and Business Economics*, *22*(3), 167–176.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50.

Fotiadis, A. K., & Stylos, N. (2017). The effects of online social networking on retail consumer dynamics in the attractions industry: The case of 'E-da' theme park, Taiwan. *Technological Forecasting and Social Change*, *124*, 283–294.

Gardner, B. (2015). Defining and measuring the habit impulse: Response to commentaries. *Health psychology review*, *9*(3), 318–322.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, *27*, 51–90.

Gupta, A., & Arora, N. (2017). Understanding determinants and barriers of mobile shopping adoption using behavioral reasoning theory. *Journal of Retailing and Consumer Services*, *36*, 1–7.

Hair, J. F., Hult, T. G. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). SAGE Publications.

Hair, J. F., Sarstedt, M., & Ringle, C. M. (2019). Rethinking some of the rethinking of partial least squares. *European Journal of Marketing*, *53*(4), 566–584.

Han, S., & Yang, H. (2018). Understanding adoption of intelligent personal assistants: A parasocial relationship perspective. *Industrial Management & Data Systems*, *118*(3), 618–636.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135.

Hernandez-Ortega, B., & Ferreira, I. (2021). How smart experiences build service loyalty: The importance of consumer love for smart voice assistants. *Psychology & Marketing*, *38*(7), 1122–1139.

Hoffmann, C. P., Lutz, C., & Ranzini, G. (2016). Privacy cynicism: A new approach to the privacy paradox. *Cyberpsychology: Journal of Psychosocial Research on Cyberspace*, *10*(4), 1–18.

Hong, I. B., & Cha, H. S. (2013). The mediating role of consumer trust in an online merchant in predicting purchase intention. *International Journal of Information Management*, *33*(6), 927–939.

Hoy, M. B. (2018). Alexa, Siri, Cortana, and more: An introduction to voice-assistants. *Medical Reference Services Quarterly*, *37*(1), 81–88.

Hsiao, C. H., Chang, J. J., & Tang, K. Y. (2016). Exploring the influential factors in continuance usage of mobile social apps: Satisfaction, habit, and customer value perspectives. *Telematics and Informatics*, *33*(2), 342–355.

Hu, T., Stafford, T. F., Kettinger, W. J., Zhang, X. P., & Dai, H. (2018). Formation and effect of social media usage habit. *Journal of Computer Information Systems*, *58*(4), 334–343.

Iranmanesh, M., Min, C. L., Senali, M. G., Nikbin, D., & Foroughi, B. (2022). Determinants of switching intention from web-based stores to retail apps: Habit as a moderator. *Journal of Retailing and Consumer Services*, *66*, 102957. https://doi.org/10.1016/j.jretconser.2022.102957

Jain, S., Basu, S., Dwivedi, Y. K., & Kaur, S. (2022). Interactive voice-assistants–Does brand credibility assuage privacy risks? *Journal of Business Research*, *139*, 701–717.

Jones, V. K. (2018). Voice-activated change: Marketing in the age of artificial intelligence and virtual assistants. *Journal of Brand Strategy*, *7*(3), 233–245.

Kang, J. W., & Namkung, Y. (2018). The effect of corporate social responsibility on brand equity and the moderating role of ethical consumerism: The case of Starbucks. *Journal of Hospitality & Tourism Research*, *42*(7), 1130–1151.

Kang, W., & Shao, B. (2023). The impact of voice-assistants' intelligent attributes on consumer well-being: Findings from PLS-SEM and fsQCA. *Journal of Retailing and Consumer Services*, *70*, 103130.

Kautish, P., Purohit, S., Filieri, R., & Dwivedi, Y. K. (2023). Examining the role of consumer motivations to use voice-assistants for fashion shopping: The mediating role of awe experience and eWOM. *Technological Forecasting and Social Change*, *190*, 122407.

Kim, D., Park, K., Park, Y., & Ahn, J. H. (2019). Willingness to provide personal information: Perspective of privacy calculus in IoT services. *Computers in Human Behavior*, *92*, 273–281.

Kim, M. S., & Kim, S. (2018). Factors influencing willingness to provide personal information for personalized recommendations. *Computers in Human Behavior*, 88, 143–152.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, 11(4), 1–10.

Kowalczuk, P. (2018). Consumer acceptance of smart speakers: A mixed methods approach. *Journal of Research in Interactive Marketing*, 12(4), 418–431.

Lalicic, L., & Weismayer, C. (2021). Consumers' reasons and perceived value co-creation of using artificial intelligence-enabled travel service agents. *Journal of Business Research*, 129, 891–901.

Laricchia, F. (2022). Number of voice assistants in use worldwide from 2019 to 2024 (in billions). Statista. Available from: https://www.statista.com/statistics/973815/worldwide-digital-voice-assistant-in-use/

Lee, J., Kim, J., & Choi, J. Y. (2019). The adoption of virtual reality devices: The technology acceptance model integrating enjoyment, social interaction, and strength of the social ties. *Telematics and Informatics*, 39, 37–48.

Lee, M. C. (2009). Factors influencing the adoption of Internet banking: An integration of TAM and TPB with perceived risk and perceived benefit. *Electronic Commerce Research and Applications*, 8(3), 130–141.

Lei, S. I., Shen, H., & Ye, S. (2021). A comparison between chatbot and human service: Customer perception and reuse intention. *International Journal of Contemporary Hospitality Management*, 33(11), 3977–3995.

Lim, W. M., Kumar, S., Verma, S., & Chaturvedi, R. (2022). Alexa, what do we know about conversational commerce? Insights from a systematic literature review. *Psychology & Marketing*, 39(6), 1129–1155.

Lim, W. M., Rasul, T., Kumar, S., & Ala, M. (2022). Past, present, and future of customer engagement. *Journal of Business Research*, 140, 439–458.

Ling, E. C., Tussyadiah, I., Tuomi, A., Stienmetz, J., & Ioannou, A. (2021). Factors influencing users' adoption and use of conversational agents: A systematic review. *Psychology & Marketing*, 38(7), 1031–1051.

Lister, K., Coughlan, T., Iniesto, F., Freear, N., & Devine, P. (2020). Accessible conversational user interfaces: Considerations for design. In *Proceedings of the 17th International Web for All Conference* (pp. 1–11).

Loureiro, S. M. C., Japutra, A., Molinillo, S., & Bilro, R. G. (2021). Stand by me: Analyzing the tourist–intelligent voice-assistant relationship quality. *International Journal of Contemporary Hospitality Management*, 33(11), 3840–3859.

Lu, B., Fan, W., & Zhou, M. (2016). Social presence, trust, and social commerce purchase intention: An empirical research. *Computers in Human Behavior*, 56, 225–237.

Lutz, C., Hoffmann, C. P., & Ranzini, G. (2020). Data capitalism and the user: An exploration of privacy cynicism in Germany. *New Media & Society*, 22(7), 1168–1187.

Lyu, T., Guo, Y., & Chen, H. (2023). Understanding people's intention to use facial recognition services: The roles of network externality and privacy cynicism. *Information Technology & People*. https://doi.org/10.1108/itp-10-2021-0817

Malodia, S., Ferraris, A., Sakashita, M., Dhir, A., & Gavurova, B. (2023). Can Alexa serve customers better? AI-driven voice-assistant service interactions. *Journal of Services Marketing*, 37(1), 25–39.

Malodia, S., Kaur, P., Ractham, P., Sakashita, M., & Dhir, A. (2022). Why do people avoid and postpone the use of voice-assistants for transactional purposes? A perspective from decision avoidance theory. *Journal of Business Research*, 146, 605–618.

Mari, A., Mandelli, A., & Algesheimer, R. (2020). The evolution of marketing in the context of voice commerce: A managerial perspective. In HCI in Business, Government and Organizations: 7th International Conference, HCIBGO 2020, Held as Part of the 22nd HCI International Conference, HCII 2020, Copenhagen, Denmark, July 19–24, 2020, Proceedings 22 (pp. 405–425). Springer International Publishing.

Mariani, M. M., Perez-Vega, R., & Wirtz, J. (2022). AI in marketing, consumer research and psychology: A systematic literature review and research agenda. *Psychology & Marketing*, 39(4), 755–776.

Maroufkhani, P., Asadi, S., Ghobakhloo, M., Jannesari, M. T., & Ismail, W. K. W. (2022). How do interactive voice assistants build brands' loyalty? *Technological Forecasting and Social Change*, 183, 121870.

McLean, G., & Osei-Frimpong, K. (2019). Hey Alexa examines the variables influencing the use of artificial intelligent in-home voice-assistants. *Computers in Human Behavior*, 99, 28–37.

McLean, G., Osei-Frimpong, K., & Barhorst, J. (2021). Alexa, do voice-assistants influence consumer brand engagement?–Examining the role of AI-powered voice-assistants in influencing consumer brand engagement. *Journal of Business Research*, 124, 312–328.

Mehta, P., Jebarajakirthy, C., Maseeh, H. I., Anubha, A., Saha, R., & Dhanda, K. (2022). Artificial intelligence in marketing: A meta-analytic review. *Psychology & Marketing*, 39(11), 2013–2038.

Min, J., & Kim, B. (2015). How are people enticed to disclose personal information despite privacy concerns in social network sites? The calculus between benefit and cost: How are people enticed to disclose personal information despite the privacy concerns in social network sites? The calculus between benefit and cost. *Journal of the Association for Information Science and Technology*, 66(4), 839–857.

Mishra, A., Shukla, A., & Sharma, S. K. (2022). Psychological determinants of users' adoption and word-of-mouth recommendations of smart voice-assistants. *International Journal of Information Management*, 67, 102413.

Moriuchi, E. (2019). Okay, Google!: An empirical study on voice-assistants on consumer engagement and loyalty. *Psychology & Marketing*, 36(5), 489–501.

Moriuchi, E. (2023). "Alexa, lock my front door": An empirical study on factors affecting consumer's satisfaction with VCA-controlled security devices. *Psychology & Marketing*, 40, 169–189.

Mostafa, R. B., & Kasamani, T. (2022). Antecedents and consequences of chatbot initial trust. *European Journal of Marketing*, 56(6), 1748–1771.

Moussawi, S., & Benbunan-Fich, R. (2020). The effect of voice and humour on users' perceptions of personal intelligent agents. *Behaviour & Information Technology*, 40(15), 1603–1626. https://doi.org/10.1080/0144929x.2020.1772368

Ofori, K. S., Larbi-Siaw, O., Fianu, E., Gladjah, R. E., & Boateng, E. O. Y. (2016). Factors influencing the continuance use of mobile social media: The effect of privacy concerns. *Journal of Cyber Security and Mobility*, 4(3), 105–124.

Oliveira, G. G., Lizarelli, F. L., Teixeira, J. G., & Mendes, G. H. S. (2023). Curb your enthusiasm: Examining the customer experience with Alexa and its marketing outcomes. *Journal of Retailing and Consumer Services*, 71, 103220.

Pal, D., Arpnikanondt, C., Funilkul, S., & Razzaque, M. A. (2021). Analyzing the adoption and diffusion of voice-enabled smart-home systems: empirical evidence from Thailand. *Universal Access in the Information Society*, 20, 797–815.

Pappas, I. O., & Woodside, A. G. (2021). Fuzzy-set Qualitative Comparative Analysis (fsQCA): Guidelines for research practice in Information Systems and marketing. *International Journal of Information Management*, 58, 102310.

Paykani, T., Rafiey, H., & Sajjadi, H. (2018). A fuzzy set qualitative comparative analysis of 131 countries: Which configuration of the structural conditions can explain health better? *International journal for equity in health*, 17, 1–13.

Perez, S. (2019). *41% of voice-assistant users have concerns about trust and privacy, report finding*. TechCrunch. https://techcrunch.com/2019/04/24/41-of-voice-assistant-users-have-concerns-about-trust-and-privacy-report-finds/

Petronio, S., & Caughlin, J. P. (2006). Communication privacy management theory: Understanding families. In D. O. Braithwaite & L. A. Baxter (Eds.), *Engaging theories in family communication: Multiple perspectives* (pp. 35–49). Sage Publications.

Pitardi, V., & Marriott, H. R. (2021). Alexa, she's not human but... Unveiling the drivers of consumers' trust in voice-based artificial intelligence. *Psychology & Marketing*, 38(4), 626–642.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903.

Poushneh, A. (2021). Humanizing voice-assistant: The impact of voice-assistant personality on consumers' attitudes and behaviors. *Journal of Retailing and Consumer Services*, 58, 102283.

Prentice, C., Loureiro, S. M. C., & Guerreiro, J. (2023). Engaging with intelligent voice assistants for wellbeing and brand attachment. *Journal of Brand Management*. https://doi.org/10.1057/s41262-023-00321-0

Ragin, C. C. (2009). *Redesigning social inquiry: Fuzzy sets and beyond*. University of Chicago Press.

Ragin, C. C., Strand, S. I., & Rubinson, C. (2008). User's guide to fuzzy-set/qualitative comparative analysis. *University of Arizona*, 87, 1–87.

Ratten, V. (2015). A cross-cultural comparison of online behavioural advertising knowledge, online privacy concerns and social networking using the technology acceptance model and social cognitive theory. *Journal of Science & Technology Policy Management*, 6(1), 25–36.

Rese, A., Baier, D., Geyer-Schulz, A., & Schreiber, S. (2017). How augmented reality apps are accepted by consumers: A comparative analysis using scales and opinions. *Technological Forecasting and Social Change*, 124, 306–319.

Bateman, R. (2020). *Voice-assistants and privacy issues*. https://www.termsfeed.com/blog/voice-assistants-privacy-issues

Rogers, R. W. (1975). A protection motivation theory of fear appeals and attitude change. *The Journal of Psychology*, 91(1), 93–114.

Ryan, J., & Casidy, R. (2018). The role of brand reputation in organic food consumption: A behavioral reasoning perspective. *Journal of Retailing and Consumer Services*, 41, 239–247.

Saad, U., Afzal, U., El-Issawi, A., & Eid, M. (2017). A model to measure QoE for virtual personal assistant. *Multimedia Tools and Applications*, 76(10), 12517–12537.

Sahu, A. K., Padhy, R. K., & Dhir, A. (2020). Envisioning the future of behavioral decision-making: A systematic literature review of behavioral reasoning theory. *Australasian Marketing Journal*, 28(4), 145–159.

Sahu, A. K., Padhy, R. K., & Dhir, A. (2022). Determinants and barriers of implementing lean manufacturing practices in MSMEs: A behavioural reasoning theory perspective. *Production Planning & Control*, 33(12), 1197–1213.

Schaufeli, W. B., Leiter, M. P., Maslach, C., & Jackson, S. E. (1996). *MBI–General Survey*. Consulting Psychologists Press.

Schomakers, E. M., Lidynia, C., & Ziefle, M. (2022). The role of privacy in the acceptance of smart technologies: Applying the privacy calculus to technology acceptance. *International Journal of Human–Computer Interaction*, 38(13), 1276–1289.

Sepasgozar, S. M. E., Hawken, S., Sargolzaei, S., & Foroozanfa, M. (2019). Implementing citizen-centric technology in developing smart cities: A model for predicting the acceptance of urban technologies. *Technological Forecasting and Social Change*, 142, 105–116.

Shin, D. H. (2010). The effects of trust, security, and privacy in social networking: A security-based approach to understand the pattern of adoption. *Interacting with Computers*, 22(5), 428–438.

Singh, S., Sahni, M. M., & Kovid, R. K. (2020). What drives FinTech adoption? A multi-method evaluation using an adapted technology acceptance model. *Management Decision*, 58(8), 1675–1697.

Sivathanu, B. (2018). Adoption of Internet of things (IOT) based wearables for healthcare of older adults—A behavioural reasoning theory (BRT) approach. *Journal of Enabling Technologies*, 12(4), 169–185.

Statista (2022). *Number of digital voice-assistants in use worldwide from 2019 to 2024 (in billions)*. https://www.statista.com/statistics/973815/worldwide-digital-voice-assistant-in-use

Stylos, N., Zwiegelaar, J., & Buhalis, D. (2021). Big data empowered agility for dynamic, volatile, and time-sensitive service industries: The case of tourism sector. *International Journal of Contemporary Hospitality Management*, 33(3), 1015–1036.

Teo, T. (2016). Modelling Facebook usage among university students in Thailand: The role of emotional attachment in an extended technology acceptance model. *Interactive Learning Environments*, 24(4), 745–757.

Trang, S., & Weiger, W. H. (2021). The perils of gamification: Does engaging with gamified services increase users' willingness to disclose personal information? *Computers in Human Behavior*, 116, 106644.

Vahdat, A., Alizadeh, A., Quach, S., & Hamelin, N. (2021). Would you like to shop via mobile app technology? The technology acceptance model, social factors and purchase intention. *Australasian Marketing Journal*, 29(2), 187–197.

Vakola, M. (2016). The reasons behind change recipients' behavioral reactions: A longitudinal investigation. *Journal of Managerial Psychology*, 31(1), 202–215.

Valaei, N., Rezaei, S., & Ismail, W. K. W. (2017). Examining learning strategies, creativity, and innovation at SMEs using fuzzy set Qualitative Comparative Analysis and PLS path modeling. *Journal of Business Research*, 70, 224–233.

van Ooijen, I., Segijn, C. M., & Opree, S. J. (2022). Privacy Cynicism and its Role in Privacy Decision-Making. *Communication Research*, 009365022110609. https://doi.org/10.1177/00936502211060984

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27, 425–478.

Vijayasarathy, L. R. (2004). Predicting consumer intentions to use on-line shopping: The case for an augmented technology acceptance model. *Information & Management*, 41(6), 747–762.

Vimalkumar, M., Sharma, S. K., Singh, J. B., & Dwivedi, Y. K. (2021). 'Okay google, what about my privacy?': User's privacy perceptions and acceptance of voice based digital assistants. *Computers fin Human Behavior*, 120, 106763. https://doi.org/10.1016/j.chb.2021.106763

Walter, J., & Abendroth, B. (2020). On the role of informational privacy in connected vehicles: A privacy-aware acceptance modelling approach for connected vehicular services. *Telematics and Informatics*, 49, 101361. https://doi.org/10.1016/j.tele.2020.101361

Wandoko, W., & Panggati, I. E. (2022). The influence of digital influencer, e-WOM and information quality on customer repurchase intention toward online shop in e-marketplace during pandemic COVID-19: The mediation effect of customer trust. *Journal of Relationship Marketing*, 21(2), 148–167.

Westaby, J. D. (2005). Behavioral reasoning theory: Identifying new linkages underlying intentions and behavior. *Organizational Behavior and Human Decision Processes*, 98(2), 97–120.

Whang, C., & Im, H. (2021). "I Like Your Suggestion!" the role of humanlikeness and parasocial relationship on the website versus voice shopper's perception of recommendations. *Psychology & Marketing*, 38(4), 581–595.

Xu, F., Michael, K., & Chen, X. (2013). Factors affecting privacy disclosure on social network sites: An integrated model. *Electronic Commerce Research*, *13*(2), 151–168.

Xu, H., Dinev, T., Smith, J., & Hart, P. (2011). Information privacy concerns: Linking individual perceptions with institutional privacy assurances. *Journal of the Association for Information Systems*, *12*(12), 798–824.

Yan, M., Filieri, R., & Gorton, M. (2021). Continuance intention of online technologies: A systematic literature review. *International Journal of Information Management*, *58*, 102315. https://doi.org/10.1016/j.ijinfomgt.2021.102315

Ye, C., & Potter, R. (2011). The role of habit in post-adoption switching of personal information technologies: An empirical investigation. *Communications of the Association for Information Systems*, *28*(1), 35.

SUPPORTING INFORMATION

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