Alexa, may I adopt you? The role of voice assistant empathy and user-perceived risk in customer service delivery

Kesha K. Coker
Department of Marketing, Miller College of Business, Ball State University, Muncie, Indiana, USA, and
Ramendra Thakur
Department of Marketing, University of Louisiana at Lafayette, Lafayette, Louisiana, USA

Abstract

Purpose – Powered by artificial intelligence, voice assistants (VAs), such as Alexa, Siri and Cortona, are at early-stage adoption rates in service contexts. Customers express hesitance in using the technology. Furthermore, the effect of a relevant variable (VA empathy) as a determinant of VAs is not widely researched. This study aims to extend the unified theory of acceptance and use of technology (UTAUT) and social response theory (SRT) to propose and test a conceptual model of the role of customer perceptions of VA empathy and risk on VA adoption and usage intensity.

Design/methodology/approach – In this study, data were collected from 387 VA users in the USA using a survey administered through Amazon MTurk. Data cleaning retained a final $n = 318$ for structural equation modeling analysis.

Findings – Findings show that perceived VA empathy enhances customers' attitude toward VA and drives adoption, thereby increasing VA usage intensity. Perceived risk is a moderator; users with high perceptions of VA empathy have greater VA adoption rates when they have high (vs low) risk perceptions of using VA.

Originality/value – This research is one of the first known studies to provide empirical evidence of the role of customer perceptions of VA empathy and risk on VA adoption in service delivery. It goes beyond VA adoption research to provide empirical evidence of the impact of VA adoption on actual usage intensity. By extending the UTAUT and SRT, this research adds to the theoretical foundation for research on VA adoption, offering practical insights for firms regarding empathetic VA design to enhance customer service delivery.

Keywords Customer service, Structural equation modeling, Service delivery, Artificial intelligence, Technology and service

Paper type Research paper

1. Introduction

With the rapid proliferation of artificial intelligence (AI) technologies, voice assistants (VAs) have become a formal component in customers' everyday lives, offering opportunities for marketers to deliver better customer service. VAs are voice-based interfaces that use voice commands to receive and interpret voice instructions (Dellaert *et al.*, 2020). These technologies rely on AI to respond to customers' voices to answer questions, provide information and place orders for goods and services. Examples include Amazon's Alexa, Google's "Hey Google," Apple's Siri and Microsoft's Cortana. These assistants are integrated into many mobile and interactive devices, including phones (e.g. Siri in iPhones) and computers (e.g. Alexa and Cortana in laptops). Voice-activated technology is also being integrated into chatbot technology, such as ChatGPT's Whisper Application Programming Interface that adds speech-to-text features to the chatbot. With such integration to accessible technologies, VAs can allow customers access to customer service at the touch of a button, anytime and anywhere.

According to Statista (2023), 4.2 billion digital VAs were used globally in 2020, and this number is expected to grow to 8.4 billion by 2024. Statista also approximated 120 million VA users in the USA in 2021 and predicted 130 million users in 2025. People use VAs not only to search the internet or a website for information (e.g. Siri, what is the weather today?) but also to purchase products online (e.g. Alexa, get me a donut) (Canziani and MacSween, 2021; Roggeveen and Sethuraman, 2020). Statistic predicts that the global voice technology market will reach a projected $50bn in 2029, approximately a 317% increase from $12bn in 2022 (Thormundsson, 2023). Voice commerce, which entails customers using voice recognition technology for goods and services online shopping, is projected to reach $20bn globally in 2023 (Statista, 2023). With 30% of US consumers owning a mobile-connected device (e.g. smart speakers), VAs emerge as a channel for firms to deliver shopping experiences through voice commerce (Statista, 2023).

Despite its exponential growth, VA is a relatively new technology (Moriuchi, 2019), with the adoption of the

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technology by customers for service interactions in its early stages. Thus, the question facing firms is:

Q1. How to design VAs to augment customer adoption and usage intensity for better shopping and customer service experiences?

Past research presents a preview of why customers use VAs in marketing applications (Dellaert *et al.*, 2020; Malodia *et al.*, 2021), exploring VA usage motivations (McLean and Osei-Frimpong, 2019), users' expertise (Fernandes and Oliveira, 2021), perceived device credibility (Flavián *et al.*, 2023) and effects of VA on consumer purchases (Sun *et al.*, 2019). However, scholars note that much VA research remains conceptual (Grewal *et al.*, 2022), with more to be learned about VA adoption (Fernandes and Oliveira, 2021; Mishra *et al.*, 2022), especially as no one technology acceptance model (TAM) captures the essence of VA. In a departure from traditional TAMs, Dwivedi *et al.* (2019) proposed that attitude is central to VA adoption and use. Yet, little is known about antecedents to attitude in VA adoption and use (Mishra *et al.*, 2022).

VA technology remains a machine without a heart. At the heart of VA technology is the power of AI, but empathetic AI is yet to become a reality (Esmaeilzadeh and Vaezi, 2022). Though researchers have conceptualized the potential benefits of empathetic VA (Dellaert *et al.*, 2020), researchers note that the outcomes of empathetic VA remain underexplored (Gelbrich *et al.*, 2021). Furthermore, researchers note the lack of research on whether VA communications of intelligence cues, including understanding user input, impact VA evaluation and usage intentions (Grewal *et al.*, 2022). A research gap emerged from a lack of empirical evidence of the effect of VA empathy on VA adoption and usage intensity in customer service delivery. Toward this end, we focus on customer perception of a desirable idyllic feature of VA that requires much research attention – VA empathy. Thus, the present research explores the effect of a relevant and not widely researched variable (empathy) as a determinant of VAs, which adds value to the state-of-the-art on AI applications in service settings.

While customers are attracted to the allure of VA devices, they express concerns about using these devices. For example, customers point to issues associated with VA communications, such as interpretation, voice recognition and perceived risks. Though privacy remains a concern, there is a more global perception of risk factors, including those associated with buying some products using VA (PwC, 2018). As a participant in a PricewaterhouseCoopers study put it, "I would shop for simple things like dog food, toilet paper, pizza [...] but "can you order me a sweater?" That's too risky" (PwC, 2018, p. 6). Five years later, a PYMNTS (2023) study reports a poor VA experience for customers. Customers prefer using VAs for simpler, low-risk tasks (e.g. playing music, setting alarms and reminders, getting driving directions) than complex, high-risk tasks associated with data breaches and errors (e.g. applying for a mortgage, opening or closing a bank account and paying for a purchase) (PYMNTS, 2023). Customers are also concerned about other issues, such as voice cloning (where fraudsters use a recording of a person's voice) when using "fintech" (financial technology) services, such as Capital One's Alexa integration for voice payments, balance checks and expense tracking (Hughes, 2023). However, there is a research gap in the literature, where very little is known about the moderating role of perceived risk on empathy and attitude toward VAs in adopting the technology. Thus, the present research explores the role of perceived risk as a global perception, as was done in the services literature (Laroche *et al.*, 2003).

The present study adds to the growing body of services literature on empathetic AI and VAs by examining the technology's empathy as a key antecedent of adoption and usage intensity. In addition, it explores perceived risk as a potential moderator. Grounded on the literature, we propose a conceptual model of the role of perceived VA empathy and user attitude toward VA in VA adoption and, consequently, usage intensity. We test this conceptual model using data collected from a sample of US VA users.

The rest of the manuscript is structured as follows. In Section 2, we develop a conceptual model and research hypotheses on the role of VAs in customer adoption and usage intensity. Then, in Section 3, we describe the method of study with data collected from the USA and in Section 4, we present the results of the study. Finally, in Section 5, we discuss the findings with their theoretical and practical implications in service settings and offer directions for future research.

2. Conceptual model and hypotheses

2.1 Perceived voice assistant empathy

In service settings, AI in its most intelligent form would be empathetic – it would feel or exhibit behaviors that suggest feelings (Huang and Rust, 2018) from machine learning (Huang and Rust, 2021). We adopt the definition of artificial empathy as "the codification of human cognitive and affective empathy through computational models in the design and implementation of AI agents" (Liu-Thompkins *et al.*, 2022, p. 1201). Since VA empathy is yet to become a reality, we refine this definition to emphasize that VA empathy is the user's *perception* of the ability of the VA to understand users and their needs and feelings in various situational contexts.

Given the lack of conceptualization and empirical research on empathy by VAs, we turn to extant research on empathy by AI, on which VAs are designed. Past research in the services literature suggests the potential benefits of empathetic AI in customer response to the technology. For example, Esmaeilzadeh and Vaezi (2022) propose that empathetic AI increases the adoption and use of AI service agents. Furthermore, Liu-Thompkins *et al.* (2022) found that empathetic AI narrows the human-AI customer service gap for affective customer experience quality. Though there is much less research in the VA context on empathy, Gelbrich *et al.* (2021) found that when customers perceive the digital assistant as emotionally supportive, their perception of its warmth increases, thereby enhancing customer satisfaction.

Given this past research, we propose that consumers who view the VA as empathetic will also show positive feelings toward the technology during service interactions. This expectation is grounded on social response theory (SRT) (Nass and Moon, 2000), where users reciprocate to a social robot that has helped them. Thus, we expect that when customers perceive that the VA is empathetic toward them during service

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interaction, they will respond in kind by showing positive feelings toward the VA. Thus, we posit:

H1a. Customers' perceived VA empathy will have a positive effect on attitude toward VAs.

Extant research also suggests that perceptions of emotions conveyed by AI technology influence customers' use of the technology. For example, Lv *et al.* (2022) found that customers in high-empathy (vs low-empathy) response scenarios show higher intentions to continuously use AI. However, there is scant empirical research in the services literature on the role of empathy in the adoption of VAs. One study to date comes close to showing this link, finding that digital assistant emotional support enhances behavioral outcomes, such as customer task persistence (Gelbrich *et al.*, 2021). Other research on the empathy-adoption link remains largely conceptual (Dellaert *et al.*, 2020; Ling *et al.*, 2021). Such research is built on the tenets of the unified theory of acceptance and use of technology (UTAUT) (Venkatesh, 2022) in AI employee adoption settings, which posits that employees' perceptions of AI technology characteristics determine user AI adoption and use. Though empathy is not identified in the UTAUT, we propose that perception of this technology characteristic determines customer use of VAs. Therefore, we hypothesize the following:

H1b. Customers' perceived VA empathy will have a positive effect on the adoption of VAs.

2.2 Attitude toward voice assistants

The marketing literature shows a robust relationship between attitude and behavior based on the theory of reasoned action (TRA) (Fishbein and Ajzen, 1975) and the theory of planned behavior (TPB) (Ajzen, 1991). Adapting the TRA, the TAM (Davis *et al.*, 1989) posits that people will show positive behavioral intentions and subsequently greater actual computer system use when they have favorable attitudes toward the technology. Though the original UTAUT (Venkatesh *et al.*, 2003) incorporates TRA, TPB, TAM and other theories, user attitude is notably absent from the UTAUT. As a solution, scholars conceptualize but are yet to empirically show, a positive attitude-behavior intention link in information system (IS)/ information technology (IT) acceptance (Dwivedi *et al.*, 2019) and AI adoption (Mehta *et al.*, 2022).

Research in AI finds that customers who experience positive emotions while using AI devices are more willing to accept AI device use and pose fewer objections to using AI devices (Gursoy *et al.*, 2019). In the realm of VA research, studies show that attitude toward VAs positively influences customer loyalty (Moriuchi, 2019) and intention to use VA devices (Mishra *et al.*, 2022; Pitardi and Marriott, 2021). In Ling *et al.*'s (2021) proposed collective model of acceptance and use of intelligent conversational agents (ICAs) in service settings, user evaluation of ICAs is expected to shape ICA adoption and use. Against this theoretical background, we expect that when users have positive feelings toward the VA in service interactions, they will be welcoming of the technology and more likely to adopt it. Thus:

H2. Customers' attitude toward VAs will have a positive effect on the adoption of the VA.

2.3 Adoption of voice assistant

Several theories, including the original UTAUT (Venkatesh *et al.*, 2003) and its extensions (Blut *et al.*, 2021; Venkatesh, 2022; Venkatesh *et al.*, 2012), model behavioral intention to use technology and AI as a positive predictor of usage behavior. Furthermore, research based on several TAMs presents conceptual models on the positive role of behavior intention in IS/IT technology use (Dwivedi *et al.*, 2019) and AI adoption (Mehta *et al.*, 2022). However, little is known about the role of adoption in the actual usage of VAs in service contexts. Given past research on technology acceptance and use, we propose a VA adoption-usage link in service contexts. Furthermore, we go beyond actual usage to examine usage intensity as the "frequency of usage" of the technology (Xu *et al.*, 2017, p. 116). Given the highly interactive nature of VA technology (Dellaert *et al.*, 2020) and its relational and frequent use (Hermann, 2022), we expect that when people adopt VAs, their intensity of use of the technology will increase. Thus, by nature of the VAs, adopters may become heavy users of the technology for service interactions as follows:

H3. Customers' adoption of VAs will have a positive effect on VA usage intensity.

2.4 Perceived risk as a moderator

The marketing literature defines perceived risk in terms of the consumer's perceptions of the uncertainty and adverse consequences of buying a product (or service)" (Dowling and Staelin, 1994, p. 119). Thus, perceived risk is generally associated with two dimensions: uncertainty and negative consequences (Campbell and Goodstein, 2001; Laroche *et al.*, 2005). In extending these definitions of perceived risk, the IT literature associates the perceived risk of technology use with a potential "loss to the user (financial, psychological, physical, or social)" arising from perceived technology failure (Im *et al.*, 2008)." In the present research, perceived risk is defined as uncertainty surrounding VA adoption and use, reflecting a global perception of risk as was done in past services research (Laroche *et al.*, 2003).

The services literature finds that perceived risk plays two roles in product adoption: a direct effect and a moderator effect. For example, Lin (2022) studied the direct effect of consumers' perceived risk on patronage intentions for smart retail services. Though most TAMs treat perceived risk as a direct effect, the construct moderates the effects of perceived usefulness (weakens) and perceived ease of use (strengthens) on technology acceptance, thereby extending the UTAUT (Im *et al.*, 2008). Other studies found perceived risk as a moderator of various effects on technology adoption in service contexts, including general service settings (Dorothea Brack and Benkenstein, 2014), social assistive technologies (Khaksar *et al.*, 2021) and ride-sharing services (Raza *et al.*, 2023).

Though perceived risk is not a new construct in marketing research, its applicability to new technology research contexts is valid yet scant (Jain *et al.*, 2022). The informational technology literature notes that "the use of these of perceived risks – as moderating factors – has a long history in technology

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acceptance," but not for newer technologies (Khaksar *et al.*, 2021, p. 356). Indeed, research on VA adoption shows that perceived risk can play two roles:

1 as a direct effect on the perceived value of VAs with consequences for continued VA usage intention (Jain *et al.*, 2022; Lavado-Nalvaiz *et al.*, 2022); and
2 as a moderator of perceived VA benefits on VA usage (McLean and Osei-Frimpong, 2019).

However, there is still much to be learned about the moderating role of perceived risks on VA adoption. Thus, this study explores a global perception of perceived risk in using VAs as a moderator.

In this research, we expect that people may have preconceived risk perceptions surrounding use. However, in the face of these risk perceptions, how customers perceive the VA's empathy and attitude toward the technology may be stronger or weaker depending on risk propensity. Based on SRT (Nass and Moon, 2000), we expect customer perceptions of VA empathy during service interactions would enhance feelings toward VAs. Furthermore, if customers with high (vs low) risk perceptions in using VAs find that the VA (e.g. Alexa) is empathetic toward them, they may show higher adoption rates. Similarly, those customers with high (vs low) risk perceptions in using VAs (e.g. uncertain about using Alexa) while holding favorable attitudes toward the VAs (e.g. feeling positively toward Alexa) may be more inclined to adopt the technology. Thus, VA empathy and attitudes toward VAs may serve as facilitators of the adoption of the VA for customers with high perceived risks in using VAs, helping to mitigate barriers to customer VA adoption in service interactions. Given this rationale, we expect perceived risk to be a moderator, enhancing the positive effects of VA empathy perceptions and attitude toward VAs for users with high (vs low) risk perceptions. Thus, we posit the following:

H4a. Customers' perceived risk in using VA will moderate the relationship between perceived VA empathy and adoption of the VA, such that this relationship will be stronger for customers with high (vs low) risk perceptions.

H4b. Customers' perceived risk in using VA will moderate the relationship between attitude toward VAs and adoption of the VA, such that this relationship will be stronger for customers with high (vs low) risk perceptions.

Based on the literature and the theory, we propose a conceptual model (see Figure 1).

3. Methodology

3.1 Procedure and participants

We collected data from Amazon Mechanical Turk (MTurk) workers. We used MTurk because data collected through this online data collection service are easy to collect, reliable, generalizable (due to access to a large population of willing participants for research studies) and as accurate as data collected using other traditional survey methods (Keith *et al.*, 2017). The data were collected from US users over 18 who have used VA, such as Microsoft's Cortana, Amazon's Alexa, Apple's Siri and Google's Hey Google.

Two screening questions were used to collect data from participants who were serious about the study. First, we asked participants to provide their ages and the state where they live. Second, at the end of the survey, we asked participants to provide their birth year and zip code. This information helped us validate data to ensure consistency in responses. Data from participants who provided their correct year of birth and zip code were considered for analysis.

Data were collected from a total of 387 participants. Of these participants, only 318 indicated that they had used VA, and data from those participants were retained for analysis. The top six reasons for using VA, as indicated by participants, were searching for products or services (66.4%), checking weather/traffic (65.4%), listening to music (66.4%), setting reminders (52.5%), checking the news (44.3%) and shopping for products or services (40.3%). An approximately equal number of males and females (51% vs. 48.2%) participated in this study. Most participants (approximately 69.5%) had a bachelor's degree or above. Approximately 88%, 6.8%, 3.9% and 1.3% indicated their ethnicity as White, African American, Asian and others, respectively.

Before conducting the confirmatory factor analysis (CFA), we used procedural and statistical methods to test for the common method bias (Podsakoff *et al.*, 2003). Results indicated that common method bias was not an issue.

3.2 Measures

Existing scales from the literature were adapted to measure the underlying constructs to fit this study. Perceived VA empathy ($\alpha = 0.93$) and attitude toward VAs ($\alpha = 0.91$) were measured using four-item and three-item seven-point Likert scales adopted from Plank *et al.* (1996) and Park *et al.* (2000), respectively. Adoption of VAs and VA usage intensity were measured using two-item and three-item scales, respectively. The items used to measure the adoption of VAs were: How many VA technologies do you own? (1 = do not own, 2 = own one, 3 = own 2–5, 4 = own 6–10, 5 = own 11–20 and 6 = own more than 20) and How long have you been using VA technology? (1 = less than 1 year, 2 = 1–2 years, 3 = 2–3 years, 4 = 3–4 years, 5 = 4–5 years and 6 = more than 5 years). Only data from those subjects who indicated owning a VA were considered for measuring this construct. VA usage Intensity ($\alpha = 0.86$) was measured using three items:

1 How frequently do you use VA technology? (1 = never, 2 = rarely, 3 = sometimes, 4 = very often and 5 = always);
2 How many times a day do you use VA? (1 = do not use it, 2 = once/day, 3 = 2-5 times/day, 4 = 6-10 times/day, 5 = 11-20 times/day and 6 = more than 20 times/day); and
3 How often do you use VA? (1 = never, 2 = rarely, 3 = sometimes, 4 = very often and 5 = always).

As was done by Laroche *et al.* (2003), a global measure of risk was used to assess perceived risk in using VAs ($\alpha = 0.89$) was measured using a five-item seven-point Likert scale adapted from Laroche *et al.* (2005) and Campbell and Goodstein (2001).

3.3 Common method bias test

This study relied exclusively on data collected through a questionnaire based on consumers' subjective perceptions.

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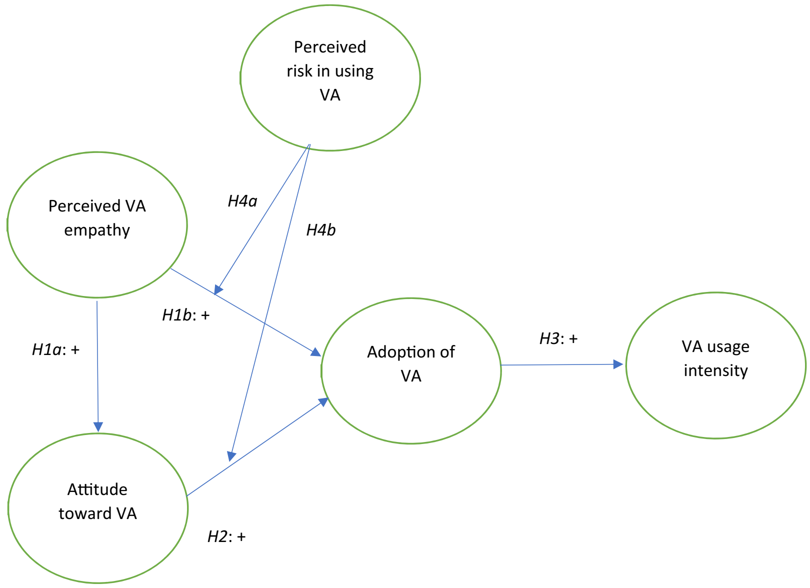
Figure 1 Conceptual model



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This reliance on self-reported data raises the potential for common method variance, which could introduce observational errors or biased estimates (Podsakoff *et al.*, 2003). Both procedural and statistical methods were used to mitigate these concerns.

Regarding procedural methods, participants were informed about the anonymous nature of their responses to reduce the likelihood of dishonesty. Additionally, questions were arranged without any apparent order or logic to ensure that subjects could not guess the intentions of the study.

Statistically, the presence of common method variance is typically indicated when a single factor emerges in exploratory factor analysis or explains most of the covariance between variables (Malhotra *et al.*, 2006). In this study, exploratory factor analysis revealed a solution formed of four latent variables, collectively accounting for 81.14% of the model variance, with the largest factor explaining 47.75%. Therefore, it is reasonable to conclude that there are no problems related to common method bias in this study.

Furthermore, we conducted Harman's single-factor test as an additional measure to assess the potential existence of common method bias (Podsakoff *et al.*, 2003). In this test, all 12 items used in this study were subjected to an un-rotated principle-component factor analysis to force them onto a single factor. The results showed that the single factor accounted for less than 50% of the variance, providing evidence that common method bias was not a problem.

4. Results

Structural equation modeling using EQS 6.2 software was used for analysis. First, we estimated the measurement model and then the structural model. The CFA results for the measurement model indicated factor loadings ranged between 0.61 and 0.88, suggesting that all items were loaded on their individual constructs, signifying that the constructs were unidimensional. We also assessed convergent and discriminant validity. Results indicated that the average variance extracted (AVE) for all the constructs was greater than the recommended value of 0.50 (Fornell and Larcker, 1981), consequently confirming convergent validity (see Table 1). The results also indicated that the square root of the AVE between the constructs was greater than the correlations between the constructs, satisfying discriminant validity (Fornell and Larcker, 1981) (see Table 2).

Next, we tested the structural model. The fit indices for the structural model indicated acceptable goodness of fit. The Satorra–Bentler scaled Chi-square index was significant (S–Bχ^2 = 122.43, df = 50, $p < 0.000$), and the RMSEA value was 0.068, showing acceptable model fit. The other model fit indices (CFI = 0.96, NNFI = 0.95, NFI = 0.94 and IFI = 0.96) were above the recommended value of 0.90 (Baumgartner and Homburg, 1996), displaying good model fit.

4.1 Direct effects of perceived voice assistant empathy and attitude toward voice assistants

Once the measurement model was confirmed, we tested the causal relationships between the four constructs (perceived VA empathy, attitude toward Vas, adoption of Vas and VA usage intensity) and the hypothesized paths for significance. First, the directionality of the parameters was inspected, and then the path's magnitude between the constructs was examined. The results indicated that all four hypothesized paths tested in this study were significant and in the hypothesized directions. Figure 2 shows the structural model results from testing *H1* to *H3* on the direct effects of constructs on VA adoption and usage intensity. The direct effect of perceived VA empathy on attitude toward Vas ($\beta = 0.38$, $p < 0.01$) and adoption of VA ($\beta = 0.24$, $p < 0.01$) is positive and significant, supporting *H1a* and *H1b*. Results also show the paths from attitude toward Vas to adoption of the VA ($\beta = 0.64$, $p < 0.01$) and adoption of the VA

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Table 1 Measurement model results

Construct	Sample size ($N = 318$) Loading	CR
Perceived VA empathy		0.93
1. VA technology understands my feelings about my situation	0.88	
2. VA technology is on the same wavelength as me	0.89	
3. VA technology seems to understand what I need	0.81	
4. VA technology always understands my needs	0.88	
Attitude toward VAs		0.86
1. Unpleasant ———— Pleasant	0.76	
2. Bad ———— Good	0.87	
3. Unfavorable ———— Favorable	0.82	
Adoption of VAs		0.69
1. How many VA technologies do you own?	0.61	
2. How long have you been using VA technology?	0.83	
VA usage intensity		0.84
1. How frequently do you use VA technology?	0.83	
2. How many times a day do you use VA technology?	0.72	
3. How often do you use VA technology?	0.85	
Perceived risk in using VAs		0.91
1. I feel like I am taking a risk by using VA technologies	0.77	
2. I am cautious about using VA technologies	0.87	
3. I would rather be safe than sorry in using VA technologies	0.81	
4. I am not a risk taker when using VA technologies	0.83	
5. I will not take chances in using VA technologies	0.83	

Notes: All factor loadings are significant at $p < 0.05$; CR = composite reliability
Source: Authors' own work

Table 2 Construct correlations and AVEs

Constructs	1	2	3	4
	Sample size ($N = 318$)			
1. Perceived VA empathy	*0.81*	0.51	0.01	0.45
2. Attitude toward VA		*0.74*	0.20	0.59
3. Adoption of VA			*0.86*	0.35
4. VA usage intensity				*0.89*
AVE	0.75	0.67	0.53	0.64

Notes: AVE = average variance extracted. Correlation is significant at the 0.01 level (two-tailed). Diagonal elements represent the square root of the AVE between the constructs. For discriminant validity, diagonal elements should be larger than off-diagonal elements
Source: Authors' own work

to VA usage intensity ($\beta = 0.99, p < 0.01$) are significant, therefore supporting *H2* and *H3*.

4.2 Moderating effect of perceived risk in using voice assistants

We used Hayes's (2013) process macro approach for testing moderation and followed the approach for testing for moderator effects by Boisvert and Ashill (2011). We used the factor score for these three constructs to test if the perceived risk in using VA moderates the relationship between perceived VA empathy and adoption of VA. Then, we conducted a hierarchical linear regression to test the moderating role of perceived risk in using VA on the relationship between perceived VA empathy and adoption of VA. The first step included empathy and perceived risk variables. These variables accounted for a significant amount of variance in adoption [$R^2 = 0.20, F(2,315) = 6.49, p < 0.002$]. Then, we added the interaction term between empathy and perceived risk to the regression model, which accounted for a significant proportion of variance in adoption [$\Delta R^2 = 0.028, F(1,314) = 9.26, p < 0.03$; $b = 0.052, t(314) = 3.043, p < 0.03$]. The interaction plot shows that perceived risk moderates the relationship between empathy and adoption. Hence, this relationship is stronger when customers perceive high-risk (vs low-risk) in using VA technology, thereby supporting *H4a* (see Figure 3).

To test perceived risk as a moderator of the effect of attitude toward Vas on adoption, in step one, we included attitude and perceived risk in using VA in the regression equation. Results show that attitude and perceived risk account for a significant amount of variance in adoption [$R^2 = 0.26, F(2,315) = 11.71, p < 0.001$]. In the next step, when the interaction term between attitude and perceived risk was added to the regression model, results indicated a nonsignificant proportion of variance in adoption [$\Delta R^2 = 0.002, F(1,314) = 0.831, p > 0.05$; $b = 0.021, t(314) = 0.912, p > 0.05$]. These results suggest that perceived risk *does not moderate* the

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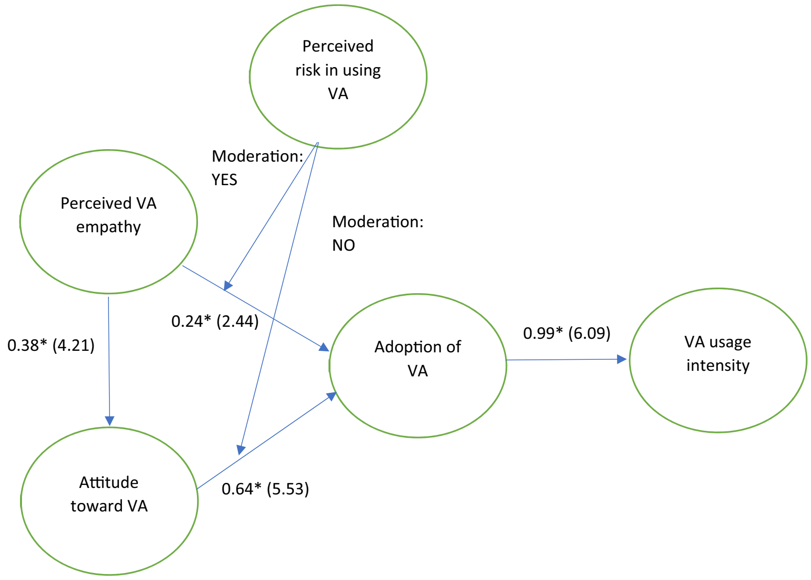
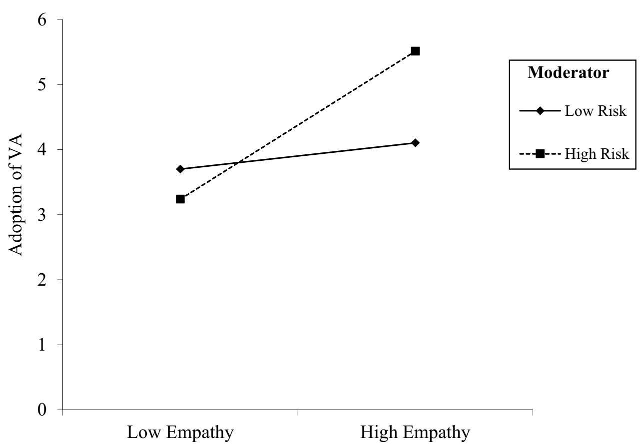
Figure 2 Structural model results



Note: * = $p < 0.01$
Source: Authors' own work

Figure 3 Moderation results



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relationship between attitude and adoption of VA technology, therefore not supporting *H4b*.

5. Discussion

The significance of VA empathy has largely been overlooked in academic research. This study aims to answer questions related to the impact of perceived VA empathy, attitude toward VA and customer-perceived risk on VA adoption and usage intensity. Much of the existing research on VA research has remained conceptual (Grewal *et al.*, 2022), with researchers highlighting the unchartered territory regarding the outcomes associated with empathetic Vas (Gelbrich *et al.*, 2021). In this context, our research contributes to the literature by proposing and testing a conceptual model of the roles of customers' perceptions of VA empathy and risk on VA adoption and usage intensity.

The results indicate that when users perceive the VA as empathetic, they have a positive attitude toward Vas and greater adoption intention, thereby increasing their VA usage intensity. Moreover, this study identifies customers' perceived risk in using VA as a moderator, suggesting that users with high perceptions of VA empathy are more likely to adopt Vas when they also have high-risk perceptions of using VA. In summary, this research sheds light on the evolving landscape of VA adoption in service contexts. It underscores the significance of VA empathy, customer attitude and perceived risk in influencing adoption and usage intensity.

5.1 Theoretical implications

This research makes four contributions to the services literature. First, this research contributes to emerging empirical research on VA adoption by extending the original UTAUT (Venkatesh *et al.*, 2003) and SRT (Nass and Moon, 2000) to service interactions through the lens of user perceptions of VA empathy. The UTAUT states that performance expectancy, effort expectancy, social influence and facilitating conditions affect technology adoption, which are an individual's perceptions of oneself. Our research extends the UTAUT by adding perceived VA empathy as an individual's perception of the technology predicting technology adoption and use. Our study also extends SRT, which postulates that individuals evaluate social cues to generate an emotional response, which shapes their behaviors. Our study shows that individuals who perceive VA as empathetic are more likely to adopt the technology. As a result, incorporating perceived technology empathy into SRT can enrich our understanding of the human-technology relationship in service interactions.

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Second, to the best of our knowledge, our study is one of the first to empirically prove the relationship between perceived VA empathy and adoption in the services literature. Thus, we add empirical evidence to support past VA research on adoption, which is primarily conceptual (Dellaert *et al.*, 2020; Ling *et al.*, 2021). Our research also introduces the attitude toward VA, a construct that scholars note is absent from many TAMs (Dwivedi *et al.*, 2019; Mehta *et al.*, 2022). Our study extends the literature by empirically showing how VA empathy affects not only adoption but also consumers' attitude toward VA, thus filling the gap in the services literature.

Third, our research goes one step beyond adoption to examine the intensity of VA use, defined as the frequency and extent of use in service interactions. Thus, we extend past research on adoption or behavioral intention as the outcome variable. Finally, we found that perceived risk moderates the relationship between VA empathy and adoption, thus suggesting that users with high perceptions of VA empathy have greater VA adoption rates when they have high (vs low) risk perceptions in using VA. Interestingly, our study found that perceived risk does not moderate the relationship between attitude and adoption, thus suggesting that this relationship exists irrespective of perceived risk in using VA.

5.2 Managerial implications

Our study presents managers with insights into how to build VA technology for adoption in service contexts. First, since our study found that perceived VA empathy positively influences adoption, managers should incorporate features to make the VA appear more empathetic to users. For example, managers could make the VA more active listeners and adjust the tone of the VA's voice according to the user's mood. VA should also be designed to understand the context of the conversation. By incorporating these features in the VA, the users may be encouraged to use this technology, which will enhance adoption and eventually increase usage intensity.

Second, managers should try to understand customers' level of comfort or risk tolerance with VA in service interactions. With personalization features, the VA itself may be able to detect the customers' risk-tolerance with its AI machine learning features and adapt to suit. Building perceptions of empathetic VA may call for developing design features that make the VA responsive to users' needs based on the situational context. Increasing perceptions of VA empathy can then mitigate the impact of risk for customers with high-risk perceptions, providing a viable solution to the personalization-privacy paradox of using VAs.

5.3 Limitations and future research

Given that this research is among the first to explore the direct effect of VA empathy and the moderating effect of perceived risk in service contexts, a few limitations provide lucrative avenues for future research. The limitations of this study with future research opportunities can be classified into two categories: data collection limitations and limitations related to this study's scope.

5.3.1 Data collection limitations

Data collection limitations give rise to four concerns:

1 sampling;
2 result generalizability;
3 cross-cultural analysis; and
4 generational cohort analysis.

First, regarding sampling issues, the data collected for this study entailed the survey method with self-reported data from a general population of US VA users. This data collection method may have introduced certain biases commonly found in studies drawing on self-reported data by participants. For example, self-reported data collected through surveys may lead to social desirability bias, where the participant may answer the questions in ways they believe to be socially acceptable. Thus, future research may use experimental designs with lab studies to capture customers' real-time interactions with specific VAs in service contexts, such as VAs with Alexa, Siri or Microsoft's Cortana, in a simulated financial service or other customer service interaction. Additionally, a mixed-method research design may collect rich qualitative data that delves deeper into and extends findings from the present research.

Second, as the data for this study were collected from a general population of VA users in the USA, the result of this study may not be generalizable to VA users worldwide. Third, and relatedly, because this study's data was limited to the US geographic region, it precludes cross-cultural analyses of VA users. Therefore, future research may explore VA adoption and usage across countries and cultures. Future extensions of this study may collect data from different geographical regions where service interactions may be more human-based than driven by AI-based VAs. Future research can extend the present study's findings to better understand the impact of cultural dimensions, such as individualistic vs collectivist, on VA adoption and usage intensity in service contexts.

Finally, segmentation issues emerge due to the data collected from a general population of VA users in the USA, without regard to generational cohort groups. Therefore, the results of this study can be generalized only to the US population and not across specific US generational cohorts. Therefore, future research may segment the general population to study specific groups of users, such as Millennials, Generation Z or across other generational cohorts, to better understand VA adoption and use behavior by different customer segments in service contexts. Future research may also compare generational cohorts to explore whether differences exist in the roles of perceived VA empath and risk in VA adoption and usage intensity.

5.3.2 Limitations related to this study's scope

Limitations in this study's scope stem from a restricted exploration of moderators and unexplored modalities of VA interactions in service contexts. First, this study only explored perceived risk as a moderator of VA adoption, leaving out other unexplored moderators beyond this study's current scope. Future research may investigate other moderators, such as VA modality and situational context of VA usage throughout the customer journey in the service interaction.

Second, this research leaves much to be learned about unexamined VA communication modalities, such as audio-visual communications by technology. Future research may explore the impact of multimodal interaction in service contexts, such as combining voice-based interaction with touch-based interaction with visuals for an immersive user VA experience. For example, future research may explore how

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different modalities may work in devices such as the Amazon Echo Show, which incorporates touch-based audio-visual communications compared to conventional VAs, such as the Amazon Echo Dot, for audio-only communications in terms of adoption and usage.

6. Conclusion

This study advances our understanding of how VAs are adopted and used in various service contexts. With VAs such as Alexa, Siri and Cortana continuing to emerge and evolve in the early stages of adoption, customer hesitance remains a notable challenge. The results of the present study demonstrate that perceived VA empathy plays a pivotal role in shaping users' attitudes and driving adoption, ultimately leading to increased VA usage intensity. Furthermore, the results show that customers' perceived risk in using VA moderates the relationship between perceived VA empathy and adoption of VA, suggesting that individuals who perceive VAs as empathetic can still embrace VAs even in light of high-risk perceptions.

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About the authors

Kesha K. Coker is an Assistant Professor of Marketing at Ball State University. She has published in the *Journal of Business Research*, *Journal of Consumer Behaviour*, *Journal of Product and Brand Management*, *Journal of Research in Interactive Marketing*, among others. She is on the Marketing Education Review editorial board. Kesha K. Coker is the corresponding author and can be contacted at: kkcoker@bsu.edu

Ramendra Thakur is the Coca-Cola Professor of Marketing at University of Louisiana Lafayette. He has published in the *Journal of the Academy of Marketing Science*, *Industrial Marketing Management*, *European Journal of Marketing*, *Journal of Business Research*, among others. He is the Associate Editor of the *Journal of Services Marketing*.

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