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SHOPPING WITH VOICE ASSISTANTS: HOW EMPATHY AFFECTS INDIVIDUAL AND FAMILY DECISION-MAKING OUTCOMES

ABSTRACT

Artificial intelligence (AI)-enabled voice assistants (VAs) such as Amazon Alexa increasingly assist shopping decisions and exhibit empathic behavior. The advancement of empathic AI raises concerns about machines nudging consumers into purchasing undesired or unnecessary products. Yet, it is unclear how the machine's empathic behavior affects consumer responses and decision-making outcomes during voice-enabled shopping. This article draws from the service robot acceptance model (sRAM) and social response theory (SRT) and presents an individual-session experiment where families *(vs. individuals)* complete actual shopping tasks using an ad-hoc Alexa app featuring high *(vs. standard)* empathic capabilities. We apply the experimental conditions as moderators to the structural model, bridging selected functional, social-emotional, and relational variables. Our framework collocates affective empathy, explicates the bases of consumers' beliefs, and predicts behavioral outcomes. Findings demonstrate (i) an increase in consumers' perceptions, beliefs, and adoption intentions with empathic Alexa, (ii) a positive response to empathic Alexa holding constant in family settings, and (iii) an interaction effect only on the functional model dimensions whereby families show greater responses to empathic Alexa while individuals to standard Alexa.

KEYWORDS

Voice assistant; Voice commerce; Empathy; Shopping behavior; Service robot acceptance model; Social response theory; Voice app

1. Introduction

Artificial intelligence (AI) technologies enable devices to resemble various cognitive functions usually associated with the human mind. Among others, AI-based Voice Assistants (VAs) such as Amazon Alexa or Google Home can monitor human behavior, utilize algorithms to identify patterns, and predict future needs. The capacity of such devices to engage in dialogues in human language, elaborate requests in context, and dynamically expand knowledge makes them more human-like social exchange partners (van Doorn et al., 2017). Drawing on these abilities, VAs can actively nudge consumer shopping decisions while operating as personal concierges or shoppers (Hoy, 2018). These automated technologies, increasingly adopted in service management, are expected to partially replace traditional customer-salesperson interactions (Marinova et al., 2017; Wirtz et al., 2018). As a result, VAs will likely affect how services are delivered in the future and how customers and businesses interact (McLean & Osei-Frimpong, 2019; Dellaert et al., 2020), with increasing concerns by policymakers (EU Competition Policy, 2021).

With over 320 million devices installed globally, shopping-related VAs have witnessed unprecedented growth (Statista, 2021). In the US, 35% of the population already owns a VA (NPR & Edison Research, 2022), and 9% have made at least one purchase using voice-only devices (eMarketer, 2020a); this shows that the foundation is in place for shopping through VAs to grow from nearly $5 billion in 2021 to $19 billion by 2023 (Juniper Research, 2021). As VAs rapidly enter multi-user environments like our homes, AI-based features empowering family-based interactions become more popular. For instance, Alexa allows the simultaneous engagement of one or more customers, without mentioning the wake-up word, through the command "Alexa, join the conversation" (Amazon Science, 2021). Also, the VA helps all family members to create a multi-user shopping list by simply using voice (Lee et al., 2022). With VA-consumer interactions in small groups becoming common, it is critical to understand how families perceive and interact with these agents; in particular, how collective and individual behaviors (Purington et al., 2017; Ostrowski et al., 2022) as well as the motivations to use VAs differ (McLean & Osei-Frimpong, 2019; Wald et al., 2022).

As VAs increasingly display emotional intelligence traits, consumers are expected to rely on empathy in their judgment of the machine's performance (Huang & Rust, 2021). In sales, empathy was described as a salesperson's demonstration of interest and care for the customer's well-being (Parasuraman et al., 1998). Due to its positive impact on communication and interaction processes between salesperson and customer, empathy can be considered a

prerequisite to successful selling (e.g., Berry et al., 1990). Empathy creates bonds between actors, thus satisfying the need for unity and harmony by fostering feelings of affiliation and connectedness (Aaker & Williams, 1998). Once a characteristic exclusively attributed to human beings, empathy is now increasingly present in smart objects and considered a powerful tool to influence consumer decisions (McStay, 2018). However, conversational agents are in no way taking users' perspectives (cognitive empathy) in precisely the same way that humans would (Kaplan & Haenlein, 2019). Instead, current research suggests that while exhibiting caring and sympathy for humans (affective empathy), a VA may appear warmer (McLean et al., 2021) or more empathetic (Luo et al., 2019). Thus, the emotional responses to another social entity (machine) – the focus of our research – are expected to be central to the human affective system (Eisenberg et al., 2004; Liu & Sundar, 2018). For instance, in the process of sympathizing, the observer might experience a variety of affective reactions through dimensions of empathic concern such as compassion, pity, and personal distress (Davis, 1983). Given the crucial role of affective empathy in shaping consumers' perceptions, motivation, and evaluation of the service encounter (e.g., Comer & Drollinger, 1999), understanding people's empathetic reactions to state-of-the-art technologies in the era of machine-human collaboration is deemed critical not only for managers and policymakers but the society at large (Ahearne et al., 2022).

The rapid adoption of AI-based VAs as everyday interaction partners outside research laboratories has positioned them as promising research objects. The available research largely agrees that the relationship between humans and VAs is fundamentally social because it activates emotional, cognitive, and behavioral reactions usually found in human-to-human relationships (Reeves & Nass, 1996). However, extant research focuses primarily on the utilitarian motivations of using VAs, such as helping users to complete tasks, look up information, seek support, and process orders (McLean & Osei-Frimpong, 2019). Thus, further research exploring consumers' cognitive and affective reactions to VAs is required (e.g., Fernandes & Oliveira, 2021). In addition, prior studies do not thoroughly examine distinctive empathetic features of these technologies; hence, little is known about the relevance of affective empathy when AI-based agents behave as exchange partners (Hsieh & Lee, 2021; Morris et al., 2018). At the same time, VAs that offer seamless shopping capabilities are establishing the foundation for a more efficient household shopping environment (Libai et al., 2020). Yet, the use of VAs within the family context remains, at this stage, poorly examined empirically (Ostrowski et al., 2022). Overall, the lack of practical usage and shopping scenarios in which

actual, rather than expected, consumer behavior further confirms this research gap (Singh, 2021).

This paper examines how VA's empathic behavior influences consumer responses and decision-making outcomes during shopping. The mechanism of consumers' evaluation of VA lies at the heart of our theorization. We isolate this by using two moderating factors: VA empathy level (high vs. standard) and buyer type (family vs. individual). Drawing on the social response theory (SRT) and the service robot acceptance model (sRAM), we conducted a 2 x 2 between-subject and individual-session online experiment. Based on this theory integration, we predict that when Alexa provides empathetic responses, subjects' perceptions, beliefs, and behavioral intentions are more favorable than when providing standard responses. Thus, while manipulating the VA's warmth and caring features, we advance the following research question: *How do empathic AI machines affect consumer behavioral outcomes?*

Concurrently, we explore when such an effect produces negative consequences for users, at least in low-involvement purchases, during individual and collective shopping with family members. Our contribution helps managers develop performative voice shopping experiences using the persuasive power of empathy while it does emphasize relevant ethical challenges to policymakers. Methodologically, this is the first study employing a *machine behavior* perspective to develop an ad-hoc shopping app to increase the study's ecological validity. The first section of this paper provides a review of the most relevant literature. Next, we discuss the theoretical framework and moderation hypotheses, explicate the research methodology and examine the findings. We conclude with an overview of the implications for managers and policymakers.

2. Literature Review

AI-based VAs are developing at an exponential rate while altering individual and collective decision-making (Grewal et al., 2022). Advanced AI technologies, such as automatic speech recognition and natural language processing, enable VAs to perform complex tasks with and for consumers while becoming more human-like exchange partners. VA manufacturers seek to maximize the realism of voice-based conversations and ignite empathic responses in users (Crolic et al., 2021). For instance, Amazon is committed to developing social bots that converse coherently and engagingly with humans on popular topics such as sports and politics (Ram et al., 2018).

Although individuals usually do not believe conversational agents can display emotions, they respond better to agents who do (De Gennaro et al., 2020). Concurrently, people prefer agents who express empathy over those who only provide advice (Morris et al., 2018). Like humans, VAs assume a persona role having the ability to display emotions through voice and engage in casual jokes (Han & Yang, 2018). For example, Amazon's text-to-speech technology enables developers to create applications with a speech that sounds excited when a customer answers a trivia question correctly or sad when the answer is wrong. In a sense, this makes VAs pleasant and realistic conversational partners with a positive effect on consumer satisfaction (von Der Pütten et al., 2010).

Increasingly used for their shopping capabilities, VAs act as "always on" devices that can process (or even automate) tasks with a simple voice command emphasizing a bidirectional consumer interaction. The terms "voice commerce" and "voice shopping" refer to the transactional act of placing an order as well as to the technical capabilities and communicative activities that allow users to search for a product, listen to reviews, add items to a list, or track an order, among other capabilities (Mari et al., 2020). With a simple "yes" and without providing any personal information such as address or credit card details, users can buy physical products (e.g., pizza) or services (e.g., music) from third-party voice apps (so-called skills or actions) such as Domino's or Spotify. At the same time, VAs users buy groceries and durables from physical retailers partnering with the VA manufacturer (e.g., Whole Foods or Walmart) or using the default e-retailers (e.g., Amazon.com or Google Shopping). All these capabilities and partnerships broaden the resources available to consumers and streamline the shopping experience.

Despite the ease of making low-involvement purchases, voice commerce presents several practical downsides requiring user behavioral adaptations. In contrast to other digital platforms, they are designed to process one request at a time and on a turn-by-turn basis. This eliminates voice overlaps and decreases speech recognition errors; however, it does not currently favor multitasking or multiparty activities found in sensorially richer devices like computers or smartphones, which simultaneously present multiple pieces of information on a screen. Sequentially evaluating alternatives using auditory cues demands high working memory effort (Munz & Morwitz, 2019). When searching for a generic product category (broad match), product-brokering VAs like Alexa present a default option, "top search result". The VA recommends new products only if the consumer answers "No" to the assistant's direct question of "Do you want to order this?" and the purchasing process ends when a user either agrees to

purchase the item or halts the process. On Alexa, the choice is framed similarly to a pre-checked box on Internet forms; although users are not forced to make a decision, such choice architecture may produce several unanticipated effects, such as default effects and lock-in mechanisms (Mari & Algesheimer, 2021a, 2021b). This initial step towards autonomous shopping has the potential to significantly reduce (or even eliminate) the need for human decision-making (de Bellis & Johar, 2020). Social and relational capabilities in VAs may further increase their influence on consumer behavior contributions to such trends (Canziani & MacSween, 2021; Carolus et al., 2021).

2.1 Service Robot Acceptance Model (sRAM)

The technology acceptance model (TAM) was successfully used as a theoretical basis to explain user adoption and acceptance of any technology (Dwivedi et al., 2019). Initially, TAM emphasized the cognitive evaluations of functional dimensions such as perceived usefulness and perceived ease of use (Davis, 1989). Through several iterations, including the TAM 2 (Venkatesh & Davis, 2000), TAM 3 (Venkatesh & Bala, 2008), unified model of technology usage and adoption (UTAUT) (Venkatesh et al., 2003), and UTAUT2 (Venkatesh et al., 2012) it incorporated social and relational dimensions such as social norms and perceived enjoyment (Davis et al., 1992).

Recent studies have shown a tendency to leverage TAM in both its cognitive and affective perspectives to explore users' acceptance of VAs. Among the most promising TAM-inspired models, the service robot acceptance model (sRAM) by Wirtz et al. (2018) is emerging as a more comprehensive framework to assess the acceptance of AI-based automated technologies. The multidimensional conceptualization suggests that consumer adoption of service robots depends on functional, relational, and social-emotional factors (Heerink et al., 2010). The model examines consumer perceptions, beliefs, and behavioral intentions concerning the agent (or interface) delivering the service (Wirtz et al., 2018). Because VAs possess the capacity to engage consumers at a social level differently from the previous generation of automated shopping technologies (e.g., self-service ordering kiosks), consumer acceptance may depend not only on their functional performance but also on their ability to fulfill relational and social-emotional needs (Heerink et al., 2010; van Doorn et al., 2017; Wirtz et al., 2018). Fernandes and Oliveira (2021) responded to initial calls concerning the need for empirical research on customer preferences and tested millennials' acceptance of disembodied

VAs (e.g., De Keyser et al., 2019). Findings empirically validated sRAM, confirming that functional, social, and relational factors play a role in consumer adoption and presented crossover effects between them.

Exemplary research on technology acceptance offers insights that are likely transferable to VAs. However, prior studies have focused primarily on explaining adoption intention rather than the impact of those cognitive and emotional factors on the shopping decision process and outcome (Balakrishnan & Dwivedi, 2021). Concurrently, studying cognitive and affective factors influencing consumer responses to innovative consumer technologies requires a deep understanding of how technology is generally accepted. Thus, the existing literature needs to be more comprehensive to comprehend the consumer acceptance of specific agent-type (embodied VAs), -feature (empathic skills), -task (shopping), and -usage context (in-home). As such, the peculiarities of these voice-only devices require new theories or further development of those that have come into existence (Guha et al., 2022).

2.2 Social Response Theory

The social response theory offers further insights into the social-emotional and relational dimensions influencing consumer behavior. As per the computers are social actors (CASA) paradigm, individuals mindlessly attribute human-like characteristics to agents and apply human attributes (e.g., personality traits, stereotypes, and social norms) when interacting with them (Reeves & Nass, 1996). Agents are viewed as *social entity* even when possessing minimal indices of similarity with humans and scarce automation capabilities (De Keyser et al., 2019; Nass & Moon, 2000). However, social responses from consumers appear to be more assertive when anthropomorphized agents display human traits and characteristics, such as facial expressions, body gestures, or a voice (for a review, see Blut et al., 2021). In particular, the use of speech in smart objects generates physiological and affective arousal because the voice incorporates rich non-verbal cues through varying tones, intonation, speed, and emphasis on words, just as is the case in authentic human-to-human interaction (Scherer, 2003).

People can make inferences regarding emotions, attitudes, social status, and personality from vocal characteristics (Brave et al., 2005). As such, the voice leads to a “persona effect” because it gives a powerful indication of the presence of another individual (Lester et al., 1997, p. 359). When a conversational agent is perceived as having human-like characteristics, the consumer’s sense of human warmth and sociability increases (Gefen & Straub, 2004); hence,

in their role as everyday interaction partners, VAs become much more than a piece of technology and can function as realistic social actors. In that sense, when a machine is involved in real-time language production that allows engagement in unstructured dialogues with reciprocal responding, users tend to perceive oral interaction with machines more favorably than text-only interaction (Nass & Scott, 2005). This is especially so in shopping (Qiu & Benbasat, 2009).

2.3 Role of Empathy in Service Encounters

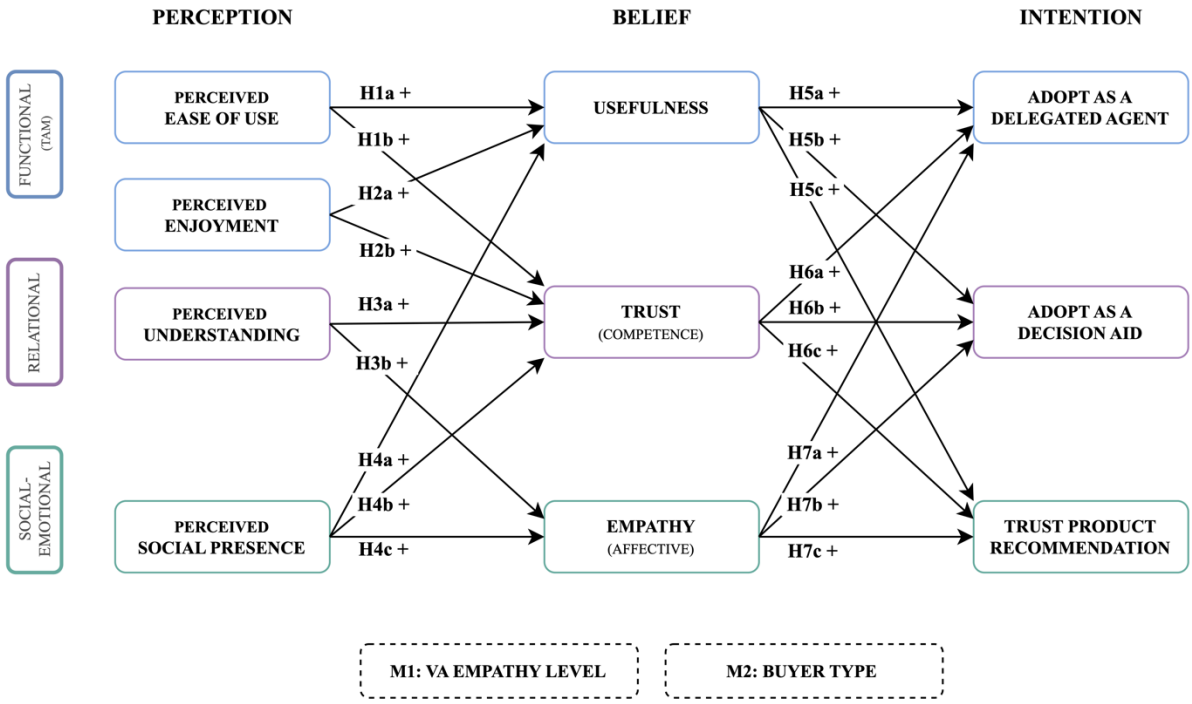
Consistent with extant research, we define empathy in relation to VAs as the individualized attention and caring prompting user's empathic responses based on the belief that a VA is warm and personal. When a human sales operator demonstrates empathy in the form of empathic understanding (Wieseke et al., 2012), the consumers' trust and confidence in the service provider increases, strengthening the attitude-behavior link (Parasuraman et al., 1988). Nevertheless, a question arises on whether the same effect materializes when the sales operator is a machine.

In an online shopping environment, agents can induce social presence with a strong positive effect on the user's trusting belief and, ultimately, willingness to accept product recommendations (Holzwarth et al., 2006). Similarly, Brave et al. (2005) discovered that manipulating empathic responses in a virtual agent increases likeability, trustworthiness, and care. As a result, when agents show higher empathy, users feel more comforted (Nguyen & Masthoff, 2009) and less frustrated (Hone, 2006), which are affective responses that would be deemed desirable in the shopping context from the perspective of the seller. However, other authors advance that the beneficial impact of empathy expression only materializes when it appropriately matches the consumer's emotional state (Ochs et al., 2008). Consequently, incongruent emotional responses may lead to a lower agent appreciation (Niculescu et al., 2013). Relatedly, the uncanny valley theory proposes that when agents show too close a resemblance to humans, negative emotional responses are aroused in users (Mori, 2012). Despite the consensus on empathy relevance in studying the affective drivers of decision-making, thus far, scholars have failed to collocate empathy in the technology adoption process and disentangle the relationships between empathy and consumer behavioral outcomes (Aggarwal et al., 2005).

3. Theoretical Framework Development

Our conceptual framework explicates the bases and consequences of consumers' beliefs towards VAs in terms of functional, relational, and social-emotional dimensions. By explicitly conceptualizing VAs as salespeople possessing empathic abilities, the framework draws on recent empirical studies focusing on the influence of VAs on consumer behavior (Fernandes & Oliveira, 2021; McLean et al., 2019; Pitardi & Marriott, 2021), and it adds to these ideas by including empathy as a mediator between perceived social presence and behavioral intentions. The model in Figure 1 depicts the integration of multidimensional variables affecting the future intention to trust a recommendation from and delegate shopping decisions to VAs. Extant research generally agrees that the extent to which a VA will be used as a delegated agent, as a decision aid, and the affective decision to trust its recommendation represent three critical consequences influencing various future shopping-related behaviors and technology adoption continuance (de Bellis & Johar, 2020; Dellaert et al., 2020; Komiak & Benbasat, 2006). Thus, they represent a success factor for VAs' diffusion and managerially relevant indicators.

Figure 1. Hypothesized Model.



3.1 Decision-making Outcomes (Behavioral Intentions)

3.1.1 Intention to Adopt as a Delegated Agent and Adopt as a Decision Aid

Similar to traditional self-service technologies, VA is an automated technology that implies a total or partial delegation of control to the machine (Candrian & Scherer, 2022). Komiak and Benbasat (2006) distinguished between two levels of intention shoppers exhibit in utilizing the VA. First, the "Intention to adopt as a delegated agent" is the degree to which a consumer is willing to *let the VA decide* what product to buy on their behalf. This delegation process implies several risks connected to the uncertain quality of the information, making consumers vulnerable to faulty decisions. In this scenario, users need to accept the recommended products without carefully examining alternative options and the rationales behind these suggestions. Second, by contrast, the "Intention to adopt as a decision aid" is the degree to which a customer is willing *to let a VA assist* with narrowing down product selection from several alternatives. Customers who want to utilize a VA as a decision aid carefully review the VA's suggestions and weigh alternatives before making the ultimate choice. This implies a lower level of dependence on the VA for decision-making than when used as a delegated agent (Komiak & Benbasat, 2006). However, when the VA is merely used to support decisions, the user is more effective (i.e., buying precisely what is needed) but less efficient (i.e., investing more time and cognitive effort) in completing the shopping tasks (Xiao & Benbasat, 2007). As VAs may simultaneously trigger both behavioral intentions in consumers, we seek to examine the factors affecting the level of customer dependence on the VA.

3.1.2 Intention to Trust VA's Product Recommendation

Based on the assumption that trust decisions usually involve reasoning and feeling, Komiak and Benbasat (2004) conceptualize trust as a combination of cognitive and emotional trust. Greenspan et al. (2000, p. 253) clarified that "Trust can be based upon the rational appraisal of a partner's reliability and competence, and upon feelings of concern and attraction". Investigating the adoption of recommendation agents, Komiak and Benbasat (2006) distinguish between cognitive trust in competence, one of the model mediators, and emotional trust. Emotional trust concerns one's assessment of beliefs and emotional reactions toward the trustee. Komiak and Benbasat (2006) position emotional trust as an evaluative affect of security and comfort about relying on an agent for the decision on what to buy. Thus, emotional trust is conceptualized as the trustor's feeling toward the behavior of relying on the trustee. Our

definition of "Intention to trust VA's product recommendation" captures the essence of emotional trust and refers to the extent to which a customer feels secure, comfortable, and confident about relying on a VA for future decisions on what to buy (Komiak & Benbasat, 2004).

3.2 Antecedents (Perceptions)

3.2.1 Perceived Ease of Use

Perceived Ease of Use (PEOU) is defined as the extent to which a person perceives the interaction with a VA to be free from effort (Davis, 1989). Autonomous shopping systems such as Amazon Alexa promise unprecedented levels of ease of use and convenience, which are expected to be strong drivers of adoption (McLean & Osei-Frimpong, 2019). The effort saved during a shopping interaction might be relocated to more rewarding life activities. Thus, Davis (1989) posits that a technological application is more likely to be accepted by users when it is perceived to be easier to use than another.

(a) Effect on Usefulness. Usefulness is the degree to which consumers believe using a particular VA will enhance their shopping abilities (Davis, 1989). Usefulness was theorized to be influenced by PEOU because "the less effortful a system is to use, the more using it can increase job performance" (Venkatesh & Davis, 2000, p. 192). Evidence supports the fact that PEOU has no direct effect on the intention to use but rather an indirect effect through usefulness (Agarwal & Prasad, 1999; Venkatesh, 1999), also in the context of VAs (Buteau & Lee, 2021).

(b) Effect on Trusting Competence. The "willingness to rely on an exchange partner in whom one has confidence" describes the multidimensional concept of trust (Moorman et al., 1993, p. 82). Functional elements of technological artifacts are important predictors of consumers' trust in online settings (Pitardi & Marriott, 2021). When a service provider exhibits effort in making an experience easy for the user, it conveys competence and trustworthiness (e.g., Lu et al., 2016). Defined as the rational appraisal of a partner's reliability and expertise, trusting competence can be conceived as the customer's expectation that a VA can provide good product recommendations (Komiak & Benbasat, 2006; McKnight et al., 2002). Hence, we hypothesize that:

H1: Perceived ease of use positively affects (a) the usefulness of VA for shopping and (b) trusting competence.

3.2.2 Perceived Enjoyment

Davis et al. (1992, p. 1113) introduced perceived enjoyment (PE) in the TAM model to describe "the extent to which the activity of using the computer is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated." Thus, PE is a form of intrinsic motivation for adopting information technology products and services (Venkatesh, 2000). Existing research considers PE a crucial hedonic measure of a user's perception of how engaging and entertaining it is to interact with a system (van der Heijden, 2004). Users' enjoyment during interaction with technology was found to influence the current and future use of various technologies such as web portals (van der Heijden, 2004) and smartphones (Zhou & Lu, 2011). This effect is particularly relevant in the context of VAs since consumers' interactions with such technology may trigger emotional rewards for fun and excitement (Pitardi & Marriott, 2021).

(a) Effect on Usefulness. Previous research suggests that when users find an e-learning system that is enjoyable to use, they are more likely to develop positive perceptions of the usefulness of the system (Abdullah et al., 2016). Given the novelty of VAs, interactions with consumers can be seen as hedonic experiences that go beyond the shopping-related task. On VAs, the interaction with an agent is expected to contribute to the user's perception of enjoyment through the delivery of optimal product recommendations and the interaction itself. Thus, the sense of enjoyment growing through the interaction with VAs can influence consumers' view of the VA's usefulness for shopping tasks.

(b) Effect on Trusting Competence. A pleasurable and fun experience of interacting with an immersive technology can affect many information processing elements while increasing the level of trust (Hwang & Kim, 2007). Although Pitardi and Marriott (2021) did not find a significant impact of PE on trust toward VAs, several other authors posit that the hedonic motivations of individuals can influence trust in the technology (Gefen & Straub, 2003; Hwang & Kim, 2007). Thus, we argue that hedonic benefits from interacting with enjoyable VAs

translate into firmer beliefs that VAs are competent and effective in providing recommendations. Hence, we posit that:

H2: Perceived enjoyment positively affects (a) the usefulness of VA for shopping and (b) trusting competence.

3.2.3 Perceived Sense of Understanding

Interpersonal relationships with a higher sense of understanding between people yield strong and more positive relationships (Bukowski et al., 1994). VAs serve as exchange partners in decision dialogs rather than mere command executors. Such a dynamic interaction process produces a perception of how well a VA understands a user's wants and needs. Thus, a good sense of understanding in the VA can represent a measure of the VA's (artificial) intelligence. It follows that the ability to collect and decode thoughts and requests from users accurately is critical to VAs achieving success in the market. Like interpersonal relationships, a high sense of understanding of what the user is trying to accomplish may lead to a more fulfilling human-VA relationship.

(a) Effect on Trusting Competence. AI-powered recommendation agents such as VAs represent a black box challenging to decode for the users (Voosen, 2017). Despite that, users have been found to employ the same trust criteria to assess the trustworthiness of an agent as if they were evaluating a human salesperson (Wang & Benbasat, 2007). How a consumer judges the level of trusting competence in VA during the shopping process is based on the perception that such an agent can correctly process requests. When users perceive a VA as capable of understanding not only our vocal utterances but also the true meaning behind them, we can expect an increase in the trustworthiness and competence beliefs of the agent.

(b) Effect on Empathy. A counterpart's ability to understand the consumer's spoken language and personal goals represents the foundation for creating empathic relationships. Empathy is centered around the individualized attention and caring a VA can offer. Thus, the more an agent exhibits natural conversational behavior, the more the user may find their social skills credible. As a result, users feel more comfortable interacting with an autonomous VA (Heerink et al.,

2009; Ki et al., 2020). In interpersonal relationships, a sense of understanding was found to contribute to social support. The more individuals try to understand another person, the more they are expected to respond attentively to their interlocutor (Trobst et al., 1994). Similarly, the assistive role of VAs, which includes inquiring about personally relevant matters, may lead to a higher perception of the VA's sense of understanding, contributing to the belief that the VA is empathic. Hence, we argue that:

H3: A perceived sense of understanding positively affects (a) trusting competence and (b) affective empathy.

3.2.4 Perceived (Automated) Social Presence

The extent to which agents make people feel as if they are in the company of another social entity is referred to as perceived Automated Social Presence (ASP) (van Doorn et al., 2017). The term "automated" is connected to the ability of technology to replace humans as service providers and social partners. How consumers evaluate and interact with VAs are primarily determined by their social presence (Pitardi & Marriott, 2021). As such, a realistic agent is expected to elicit a stronger sense of ASP (von Der Pütten et al., 2010). Extant online shopping studies suggest that social presence induced by a recommendation agent can increase users' satisfaction, trust, and, ultimately, usage intentions (e.g., Holzwarth et al., 2006; Qiu & Benbasat, 2009).

(a) Effect on Usefulness. Human-computer interaction (HCI) research has examined the impacts of social presence on adoption intentions via usefulness (Gefen & Straub, 1997). During shopping, consumers receive functional (e.g., faster and better decisions) and social-emotional benefits (e.g., feeling of warmth and closeness) that are often difficult to disentangle (Babin et al., 1995). Intuitively, when a shopper is enjoying the salesperson's company, positive feelings can be triggered that accentuate the usefulness of the salesperson's advice for the shopping decision. Accordingly, the benefits connected to perceived social presence alleviate consumers' cognitive load in searching and evaluating a large amount of product information during voice shopping (Lee et al., 2022). Hence, social presence may increase users' belief that a VA is a convenient and effective channel for shopping.

(b) Effect on Trusting Competence. Van Doorn and colleagues (2017, p. 48) propose that "consumers' inferential processes relating to competence vary as a function of the level of ASP (high vs. low) present in the service context, with downstream consequences for consumers' responses toward the service experience." Evidence of the positive effect of shoppers' perceptions of social presence on consumer trust in recommendation agents can be found in the e-commerce environment (Gefen & Straub, 2004; Lu et al., 2016). Qiu and Benbasat (2009) showed that human voice-based communication in online shopping environments could significantly influence perceived social presence, which acts favorably on consumers' trust in the VAs and behavioral intentions (Bickmore et al., 2016). Dellaert et al. (2020) suggest that a VA's sense of social presence may simultaneously increase trust in the VA and the quality of its recommendations.

(c) Effect on Empathy. For a considerable time, online commerce has been focused on efficiency maximization and mono-directionality. Social technologies like VAs are introducing the social component into the online purchasing (Lu et al., 2016). Social cues in VAs may prime the social conversation schema in receivers better than screen-based agents, making shoppers more likely to act as if they are conversing with another human (Nass & Moon, 2000). Recent research has shown the importance of social presence in enabling a sense of connection between VAs and their users. Ki et al. (2020) investigated individuals' interactions with VAs and discovered that social presence affects users' self-disclosure and social support for VAs. At the same time, van Doorn et al. (2017) suggest that customer-perceived sense of human contact when interacting with automated service agents is likely to increase empathic responses. Thus, we advance that:

H4: Perceived social presence has a positive direct effect on (a) the usefulness of VA for shopping, (b) trusting competence, and (c) affective empathy.

3.3 Mediators (Beliefs)

We predict the effect of three mediators, namely usefulness (functional), trusting competence (relational), and affective empathy (social-emotional), on three behavioral outcomes drawing on the seminal work by Komiak and Benbasat (2006).

3.3.1 Usefulness Effect

A VA is considered helpful for shopping decisions as long as it helps alleviate the consumers' load by gathering, sorting, and evaluating a vast amount of product information in increasingly complex marketplaces. These technologies are born with the promise that they free up time for users to carry out meaningful tasks. As a result, VAs are rated more or less helpful depending on how well they infer consumers' product needs and identify the items that best meet their demands.

The high degree of autonomy displayed by VAs may translate into a more favorable trust in product recommendations (de Bellis & Johar, 2020). As Dellaert et al. (2020) suggest, a frictionless decision-making process alleviates cognitive trade-offs. However, trade-offs between autonomy and efficiency may influence whether people adopt a VA as a decision aid or delegated agent. Currently, it is still being determined when shoppers choose to delegate the purchasing process to the VA rather than use it to assist the decision. Thus, we hypothesize that:

H5: Usefulness has a positive direct effect on behavioral intention to adopt as a (a) delegated agent, (b) decision aid, and (c) product recommender.

3.3.2 Trusting Competence Effect

Personal shoppers like Alexa or Genie exercise a greater influence when consumers are confident about their suggestions and the process that generated them. In line with Mayer et al. (1995), trusting beliefs towards a VA include one's perceptions about the agent's competence, benevolence, and integrity. However, following the insights from Komiak and Benbasat (2006, p. 944) that "customers are mainly concerned with whether the recommendation agent has the competence required to provide them with relevant and customized advice," this study includes only trusting beliefs in competence; that is, the user's perception that a VA has the ability, skills, and expertise to perform product recommendations effectively. In first-time or inexperienced

users, such as those in the current study, it may be challenging to appraise trust benevolence and integrity effectively.

Trusting competence in e-commerce strongly affects purchase behavior (Venkatesh & Davis, 2000). Trusting beliefs are effective mediators that influence the "intentions to engage in trust-related behaviors" (McKnight et al., 2002, p. 335). Trust helps consumers overcome risk and engage in trust-related behaviors with VAs, such as delegating tasks or accepting product recommendations (Gefen & Straub, 2004). Hence, we advance that:

H6: Trusting competence has a positive direct effect on behavioral intention to adopt as a (a) delegated agent, (b) decision aid, and (c) product recommender.

3.3.3 Empathy Effect

Extant research has shown that when a sales operator demonstrates empathy in the form of warmth and personalness, behavioral intentions toward the service provider increase (Parasuraman et al., 1988; Stock & Hoyer, 2005). VAs are more personal, connected, and accessible than previous consumer technologies (Fernandes & Oliveira, 2021). The ability to convey appropriate emotions according to societal norms is an increasingly present attribute in AI-based agents (Wirtz et al., 2018). Thus, it is reasonable to believe that the VA's effect on shopping behavior will incrementally depend on its relational and social-emotional performance (Heerink et al., 2010). When people interact with a machine for the first time, they rely on whatever information is available. The VA's ability to signal empathy and other social skills may increase its social attractiveness leading to more emotionally meaningful interactions (McLean & Osei-Frimpong, 2019; van Doorn et al., 2017).

Some studies found the critical role of perceived personalization of recommendations during voice shopping (Rhee & Choi, 2020) and the importance of the AI agent in explaining to users the reasoning behind their recommendations (Rai, 2020). While considering the mentioned studies in manipulating VA empathy level, we argue that a firmer empathy belief towards VAs results in more favorable acceptance intentions. Thus, we suggest that:

H7: Affective empathy has a positive direct effect on behavioral intention to adopt as a (a) delegated agent, (b) decision aid, and (c) product recommender.

3.4 Moderation Hypotheses Development

We conducted a 2 (VA empathy level: high vs. standard) x 2 (buyer type: family vs. individual) between-subject and individual-session experiments.

3.4.1 Alexa Empathy Level: High versus Standard

Evidence has recently been found supporting the notion that conversational agents' empathizing ability leads to users' intention to use such an agent (Lisetti et al., 2013). When studying elderly users, Heerink et al. (2010) found a positive correlation between social ability (human-like cues) and intention to use screen-based agents. Relatedly, Liu and Sundar (2018) argue that virtual agents in the form of chatbots expressing sympathy and empathy have similar impacts on individuals as when these emotive responses occur in human-to-human interactions.

On the negative side, humans may automatically infer that chatbots lack empathy, thus, perceiving bots as less trustworthy with product recommendations (Dietvorst et al., 2018). In fact, Luo et al. (2019) suggest that customers are harsh and purchase less after realizing the conversational partner is not a human. Similarly, Castelo et al. (2019) believe that customers might feel uncomfortable using AI-based agents when tasks involve intuition, affect, and subjective evaluation. Again, when presented with highly anthropomorphized agents, users might develop higher expectations for interactions than those with less human-like features. When human-like agents fail to meet the users' expectations, the intention to use them fades (Brandtzaeg & Følstad, 2017).

Drawing on the extant research on affective empathy (Liu & Sundar, 2018; Niculescu et al., 2013; Parasuraman et al., 1988), we posit that consumers display higher affective response when the VAs: (a) frame messages to convey warmth and sympathy (empathic responses), (b) ask relevant questions to get to know the user before providing recommendations (empathic listening), (c) offer proactive feedback on the choice and verifies the user's satisfaction (empathic feedback). Subsequently, we hypothesize that:

M1: VAs with higher (vs. standard) empathic levels generate stronger user perceptions, beliefs, and behavioral intention.

3.4.2 Buyer type: Family versus Individual

Differently from e-commerce and m-commerce, most suited for individual and private decision-making (McKnight et al., 2002), VAs physically placed at the core of consumers' domestic life are expected to assist collective shopping decisions. However, empirical research is yet to provide a clear understanding of human-VA interaction beyond dyadic relationships, as it requires seeing "family members as operating together rather than simply as a collection of individual emoters" (Hsiung et al., 2012, p. 230). While examining online household reviews, Purington et al. (2017) suggest that the effect of social presence is much stronger when VAs are situated amidst social relationships among multiple people. Concurrently, Lee et al. (2020) posit that VAs positively affect family dynamics by fulfilling the users' need for social integration. However, the question of how the social influence exercised by family members affects users' empathic responses in VAs remains substantially unanswered (Aw et al., 2022; Ostrowski et al., 2022; Wald et al., 2022).

We argue that the positive effect of VA empathy (predicted in M1) remains unchanged across shopping contexts: family vs. individual decision-making. As the interaction with VAs requires one group member to take a leading role, the proactive behavior of just one person, often tech-savvy or product category knowledgeable, may positively influence the entire group. The idea that emotional state and behavioral attitudes are contagious is well documented in social psychology, such as in "emotion mirroring." However, only recently was the ripple effect found when the behavior's initiator was not a human (Barsade, 2002). In particular, the agent's empathic characteristics (e.g., vulnerability) rippled through the entire group of human members and increased trust-related behaviors while improving group task performance (Sebo et al., 2018). As such, the affective and cognitive attitudes developed through the dyadic relationship between humans and machines influenced the social dynamics of the entire group. Drawing on the ripple effect, we argue that:

M2: User's positive responses to empathic VAs hold constant when shopping with other family members (vs. alone).

4. Methodology

The entire study took place online via Zoom; we used the 2nd generation Amazon Echo, the most diffused VA to date (eMarketer, 2020b). Each subject used a commercially available

device to buy batteries and pain relievers while only using generic search terms (broad match). Both product categories are widely available in online and offline retailers at similar price levels. Further, several marketing experts consider these product categories vulnerable to the rise of voice commerce marketplaces (e.g., Sterne, 2017). Purchasing data were collected using Amazon servers, and survey data were collected on Qualtrics.

4.1 Voice App Design

For the study, we designed an ad-hoc app for Alexa named *Voice Shopping* that replicates the native voice shopping process on Alexa in terms of communication, responses, and voice characteristics. Given the novelty of the technology, Alexa users still need to be able to distinguish third-party apps from Amazon-supported services (Major et al., 2021). As such, *Voice Shopping* gives users the feeling of dealing directly with Alexa throughout the interaction. A custom-built app represents an opportunity to increase ecological validity and to isolate the effect of the VA empathy level in a controlled but realistic purchase environment (Mari & Algesheimer, 2021a). *Voice Shopping* was developed in two versions following the VA empathy manipulation setting: standard and high. Alexa in the "standard" form is a replica designed through systematic machine behavior observations (Rahwan et al., 2019), while the empathic Alexa, not available on the market, was coded drawing on the previously discussed extant HCI and service management literature.

To increase the VA empathy level, the empathic Alexa upgrades the standard VA behavior by adapting communication elements (framing) and adding conversational features (dialog paths) to prime feelings of caring and sympathy. Appendix 1 shows the intent, utterance, and interaction flow coded in the two versions of the Alexa app. To achieve social-emotional goals in the empathic VA condition Alexa (i) provides more engaging and caring customary greetings, (ii) poses questions to understand personal (and household) preferences, (iii) offers additional hints and suggestions, (iv) gives feedback on the selected option, and (v) verifies the satisfaction of the user before completing the purchasing process.

4.2 Participant Recruiting and Sampling

A total of 412 families were recruited through the university research service of four major universities in Switzerland. Each family consists of one child (university student) and two parents. All families with good English command were invited via email to participate in

the study. The participants were required to be in a quiet environment with individual computers equipped with cameras and microphone. After each family registered for the study, we randomly assigned them to one of four study conditions using software for block randomization; next, we advised the students whether their parents were required to attend the study. Because all participants willingly offered to work with their families, no self-selection took place at this level. For control purposes, the order of the two product categories to be purchased on Alexa was also randomized. Participants were intentionally not selected based on their current use of VAs and voice commerce to provide a picture as close as possible to current VA in-market usage and reflect the relatively low penetration outside the US. Student samples are often used in e-commerce research (Gefen & Straub, 2004), and their demographic characteristics align with the leading voice shopping user group (eMarketer, 2020b). A pre-screening survey was run to account for the eventual intention of the participants not to buy batteries and paracetamol, among a pool of products, within the following 12 months. Among those in possession of the optimal technical requirements, we excluded study participants who failed to i) show up on time and in the communicated set up *student alone* or *together with both parents* (n = 20), ii) respond to the attention check at the beginning of the study (n = 3), iii) fill up part of the survey before completing the purchasing task (n = 2), and iv) completed the study in less than 15 minutes (n = 1).

Sample Characteristics. A total of 386 subjects were included in the analysis (Table 1). The groups *individual* ($n_{individual}$ = 151) and *family* (n_{family} = 235) are evenly assigned to the experimental treatment condition *standard* (n = 192) vs. *empathic* Alexa (n = 194). Our respondents ($M_{\text{age individual}}$ = 25; $M_{\text{age family}}$ = 44) were nearly evenly distributed in terms of gender (*Female* = 53%), nationality (*Swiss* = 33% vs. *Rest of world*, 25 different nations), and experience with VAs. In particular, 78% (n = 303) of participants have never or rarely used in-home VAs, while 10% (n = 40) use them weekly or more often. In terms of shopping behavior, a total of 80% (n = 307) of respondents had purchased something on Amazon.com at least once. In comparison, 83% (n = 319) purchased paracetamol and 91% (n = 351) had purchased AA batteries at least once in the past (any channel). In line with current industry report findings (eMarketer, 2020a), only 4% of respondents (n = 31) claimed to have purchased via VAs. The study was, on average, completed in 29:00 minutes by individual subjects and 43:42 minutes by individuals shopping as part of families. Each study participant received a standard

compensation of USD 22.00 cash (USD 66.00 per family) for a 45-minute commitment. In addition, they were given the option of collecting the purchased products.

Table 1. Sample Characteristics.

Level	**Individual** *(n = 151)*		**Family** *(n = 235)*		**Total**	
	Count	**Proportion**	**Count**	**Proportion**	**Count**	**Proportion**
Gender						
Male	69	45.7	108	46.0	177	45.9
Female	80	53.0	126	53.6	206	53.4
I prefer not to say	2	1.3	1	0.4	3	0.8
Age						
18 - 24	73	48.3	66	28.1	139	36.0
25 - 34	73	48.3	14	6.0	87	22.5
35 - 44	5	3.4	6	2.6	11	2.8
45 - 54	-	-	74	31.5	74	19.2
55 - 64	-	-	65	27.7	65	16.8
65+	-	-	10	4.3	10	2.6
Nationality						
Swiss	64	42.4	66	28.1	130	33.7
Other	87	57.6	169	71.9	256	66.3
Fq. VA usage						
- Never / Rarely	124	82.1	179	76.2	303	78.5
- Occasionally / Once a month	14	9.3	29	12.3	43	11.2
- Once a week / Daily	13	8.6	27	11.5	40	10.3
Fq. Voice Shopping						
- Never / Rarely	146	96.7	222	94.5	368	95.3
- Occasionally / Once a month	4	2.6	11	4.7	15	3.9
- Once a week / Daily	1	0.7	2	0.8	3	0.8

Note: Total of 79 families. Two members of two families were excluded from the study.

Sample size by group: Condition 1 - individual x standard VA: n = 76; Condition 2 - individual x empathic VA: n = 75; Condition 3 - family x standard VA: n = 116; Condition 4 - family x empathic VA: n = 117.

4.3 Procedure and Task

A researcher welcomed participants to the virtual room on Zoom and checked that all technical requirements were fulfilled. Three distinct stages followed the welcome. First was the introduction to the study, where the researcher presented Alexa, showed a demo, and gave instructions to participants. Then, the researcher shared a link with session participant/s containing an informed consent form and study instructions before leaving the room. Family members opened the link on their respective laptops or tablets. The second stage involved the purchasing task, where participants were asked to buy two products on Amazon Alexa in two separate sessions. The third and final stage was the online questionnaire, which involved all study participants filling out an online survey about their perceptions and attitude toward Alexa.

Task. In a randomized order, subjects purchased one packet of four AA batteries on Alexa for electronic devices such as TV remote controls, clocks, or wireless mice and one packet of painkillers paracetamol tablets 500mg (20 pieces). Individuals initiated the shopping capability by saying, "Alexa, open Voice Shopping," at which point they entered a code and searched for the product category. Entering the correct code provided in the task instruction was necessary to progress in the shopping process; thus, we consider the code a valid attention check. Participants were instructed to say "yes" when they were ready to purchase the specific option and "no" if they wanted to hear more options.

Likewise individual users, each family made only one purchase per product category. Families were self-organized in the shopping task and could exchange opinions, thoughts, and feelings within their group. Voice Shopping includes three options per product category. These options represent the top i) market leader brand (i.e., Duracell, Panadol), ii) private label by Amazon (i.e., Amazon Basics, Amazon Basic Care), and iii) generic local retailer brand (i.e., Coop, Coop Vitality). Every recommended brand was aligned with three different price points of cheap, average, and premium, which is in line with both online and brick-and-mortar Swiss retailing prices (CHF 4.95, 5.95, 6.95). As Amazon adopts an everyday low-price policy, the first option was always offered the most competitive price (CHF 4.95). In contrast, the price of the following options was randomized between CHF 5.95 and CHF 6.95. To eliminate the effect of quality and quantity, the items recommended by Alexa had the same product description and quantity. Brand name and price were the only variable factors among the available options.

4.4 Measures

We derived measures for the ten primary constructs in our study from existing scales or studies in the literature, and we adapted them to suit the research setting (voice commerce). All items in these constructs were randomized and measured using a 7-point Likert scale (1 = strongly disagree; 7 = strongly agree).

For perceived ease of use, we used a 4-item scale adapted from Venkatesh and Davis (2000), which obtained a Cronbach's alpha ranging from .86 to .98 across studies. A 3-item scale for perceived enjoyment was adapted from Abdullah et al. (2016), which in turn relied on the measures developed by Davis et al. (1992). Both studies show this measure to be reliable and valid (α = .92). We used the optimized 5-item scale of perceived sense of understanding

that Ki et al. (2020) adapted from Kumar and Benbasat (2002) to suit the VA research context; individual item loadings between 0.86 and 0.91. For perceived automated social presence, a 5-item scale was adapted from Gefen and Straub (2004), later applied to the e-commerce setting, and further validated (α = .89) by Kumar and Benbasat (2006).

Regarding the three mediators, we used an optimized 5-item scale for usefulness adapted from Van der Heijden (2004) and Adbullah et al. (2016) and initially developed by Davis (1989), who showed that this measurement is valid and reliable (α = .90). Trusting competence was measured using a 3-item scale from Komiak and Benbasat (2006), then replicated by Wang and Benbasat (2007), which relied on online trust measures developed and validated (individual loadings above .80) by McKnight et al. (2002). The affective empathy construct was operationalized with a 3-item scale asking the extent to which the VA is: (i) warm, (ii) personal in its interactions, and (ii) (overall) empathetic (Parasuraman et al., 1988; Liu & Sundar, 2018).

The measures concerning the three behavioral outcomes in this study, namely intention to adopt as a delegated agent (2 items), adopted as a decision aid (3 items), and trust product recommendations (3 items), were adapted from Komiak and Benbasat (2006) who reported all individual item loadings to be above .85.

5. Structural model

Structural equation modeling with latent variables is extensively used in marketing, HCI measurement, and hypothesis testing (Bagozzi & Yi, 1988). Models were run using the MPlus 8 program (Muthén & Muthén, 2017). We include all survey respondents when testing H1-H7. The hypothesized model was evaluated using convergent and discriminant validity tests.

5.1 Convergent and Discriminant Validity

Cronbach's alpha (α), composite reliability (CR), and average variance extracted (AVE) are measures used to evaluate the internal consistency of constructs (Fornell & Larcker, 1981). Estimates of Cronbach's alpha greater than .70, CR greater than .60, and AVE greater than .50 are usually considered to support internal consistency (Bagozzi & Yi, 1988; Hair et al., 2017). A total of 28 measures out of the original 36 are significantly greater than these stipulated criteria suggesting good convergent consistency; thus, they are included in further analysis.

We evaluated the discriminant validity of all constructs using five different approaches. First, we built a confirmatory factor analysis (CFA) model with ten latent constructs and 28 measures. The results show the goodness-of-fit for the model; see paragraph "Structural Model Estimation" (Bagozzi & Yi, 1988). Second, discriminant validity is further tested by cross-loadings using the Fornell-Larcker criterion. The results of the cross-loading analysis (Table 2) show factor loading indicators on the assigned construct being higher than all loadings of other constructs (Fornell & Larcker, 1981). Third, the square root of the AVE exceeds the inter-correlation for each latent variable (Hair et al., 2017).

Table 2. Convergent and Discriminant Validity and Correlation Matrix for Full Sample.

	CR	AVE	MSV	ASV	EOU	ENJ	SOU	SOP	USE	COM	EMP	AGE	AID	TPR
EOU	0.86	0.67	0.59	0.38	*0.82*									
ENJ	0.90	0.82	0.45	0.34	0.67	*0.91*								
SOU	0.81	0.59	0.59	0.34	0.77	0.61	*0.76*							
SOP	0.87	0.68	0.69	0.35	0.55	0.63	0.55	*0.83*						
USE	0.91	0.76	0.42	0.34	0.65	0.61	0.55	0.57	*0.87*					
COM	0.85	0.65	0.49	0.36	0.70	0.63	0.66	0.56	0.53	*0.80*				
EMP	0.88	0.71	0.69	0.33	0.54	0.57	0.58	0.83	0.51	0.53	*0.84*			
AGE	0.82	0.69	0.46	0.29	0.49	0.46	0.45	0.49	0.55	0.52	0.50	*0.83*		
AID	0.88	0.71	0.64	0.35	0.54	0.51	0.49	0.50	0.65	0.57	0.49	0.66	*0.84*	
TPR	0.94	0.85	0.64	0.39	0.59	0.55	0.55	0.55	0.64	0.67	0.55	0.68	0.80	*0.92*

Abbreviations: CR = Composite Reliability; AVE = Average Variance Extracted; MSV = Maximum Shared Variance; ASV = Average Squared Shared Variance. In italic: square root of AVE for each construct.

Note: EOU = perceived ease of use, ENJ = perceived enjoyment, SOU = perceived sense of understanding, SOP = perceived social presence, USE = usefulness, COM = trust (competence), EMP = empathy (affective), AGE = intention to adopt as a delegated agent, AID = intention to adopt as a decision aid, TPR = intention to trust product recommendation.

All correlations are significant at $p < .001$.

Fourth, the heterotrait-monotrait (HTMT) ratios (Table 3) are lower than the conventional threshold of 0.90 (Henseler et al., 2015).

Table 3. Heterotrait-Monotrait (HTMT) Ratio.

	EOU	ENJ	SOU	SOP	USE	COM	EMP	AGE	AID	TPR
EOU	1									
ENJ	0.66	1								
SOU	0.75	0.59	1							
SOP	0.54	0.63	0.56	1						
USE	0.64	0.58	0.57	0.55	1					
COM	0.68	0.60	0.66	0.55	0.60	1				
EMP	0.55	0.57	0.60	0.83	0.55	0.53	1			
AGE	0.43	0.45	0.46	0.49	0.56	0.55	0.50	1		
AID	0.56	0.59	0.54	0.56	0.65	0.56	0.48	0.66	1	
IAR	0.59	0.58	0.56	0.56	0.65	0.67	0.55	0.69	0.79	1

The mentioned tests provide evidence of discriminant validity. Finally, we performed a chi-square difference test for each pair of factors by comparing the chi-square value for a measurement model and constrained the correlation to equal one to a baseline model. Every case resulted in a significant difference suggesting that all the measures of constructs in the measurement model achieve discriminant validity (Algesheimer et al., 2005).

The final functional, relational, and social-emotional constructs with measurement items and standardized item loading are shown in Table 4.

Table 4. Summary of Measures.

Constructs	Measures (Item Loading; * p < .001)	Elements
Perceived Ease of Use *(Venkatech & Davis, 2000)*	1. The interaction with Alexa is clear and understandable. (.76*) 2. I find Alexa easy to use. (.80*) 3. I find easy to get Alexa to do what I want it to do. (.85*)	**Functional**
Perceived Enjoyment *(Davis et al., 1992)*	1. I find using Alexa enjoyable. (.95*) 2. I have fun using Alexa. (.86*)	**Functional**
Perceived Sense of Understanding *(Ki et al., 2020; based on Kumar & Benbasat, 2002)*	1. Alexa understands what I am trying to do. (.77*) 2. Alexa understands my goals. (.71*) 3. Alexa understands what I want. (.81*)	**Relational**
Perceived (Automated) Social Presence *(Kumar & Benbasat, 2006; based on Gefen & Straub, 2004)*	1. When interacting with Alexa, I feel there is a sense of human contact. (.83*) 2. When interacting with Alexa, I feel there is a sense of personalness. (.81*) 3. When interacting with Alexa, I feel there is a sense of human warmth. (.85*)	**Social-emotional**
Usefulness *(Davis, 1989)*	1. Alexa allows me to accomplish shopping tasks more quickly and more easily. (.85*) 2. Alexa increases my productivity during shopping. (.88*) 3. Alexa enhances my effectiveness during shopping. (.88*)	**Functional**
Trust (Competence) *(Komiak & Benbasat, 2006, based on McKnight et al., 2002)*	1. Alexa is an expert in assessing products. (.80*) 2. Alexa has good knowledge about products. (.79*) 3. Alexa is competent and effective in providing recommendations. (.82*)	**Relational**
Empathy (Affective) *(Liu & Sundar, 2018; Parasuraman et al., 1998)*	1. Alexa is warm. (.87*) 2. Alexa is personal in its interactions with me. (.86*) 3. Overall, I think Alexa is empathetic. (.79*)	**Social-emotional**
Intention to Adopt as a Delegated Agent *(Komiak & Benbasat, 2006)*	1. I am willing to delegate to Alexa my decision about which product to buy. (.85*) 2. I am willing to let Alexa decide which product to buy on my behalf. (.82*)	**Functional**
Intention to Adopt as a Decision Aid *(Komiak & Benbasat, 2006)*	1. I am willing to use Alexa as an aid to help with my decision about which product to buy. (.84*) 2. I am willing to let Alexa assist me in deciding which product to buy. (.83*) 3. I am willing to use Alexa as a tool that suggests to me a number of products from which I can choose. (.86*)	**Relational**
Intention to Trust Product Recommendation *(Komiak & Benbasat, 2006)*	1. I will feel comfortable to purchase products recommended to me by Alexa. (.94*) 2. I will feel confident to purchase products recommended to me by Alexa. (.90*) 3. I will feel secure to purchase products recommended to me by Alexa. (.91*)	**Social-emotional**

Table 5 summarizes construct measures' means, standard deviations, reliabilities, and internal consistency statistics.

Table 5. Summary of Statistics for Construct Measures.

Construct	Number of Items	Mean	Variance	Standard Deviation	Total Variance Explained (%)	Cronbach's α
Perceived Ease of Use	3	4.83	0.08	1.51	76.54	0.85
Perceived Enjoyment	2	4.58	0.02	1.69	90.79	0.90
Perceived Sense of Understanding	3	4.30	0.09	1.53	72.12	0.81
Perceived (Automated) Social Presence	3	3.08	0.02	1.66	79.07	0.87
Usefulness	3	3.77	0.06	1.76	83.85	0.90
Trust (Competence)	3	4.25	0.08	1.55	60.32	0.85
Empathy (Affective)	3	3.08	0.00	1.64	80.30	0.88
Intention to Adopt as a Delegated Agent	2	2.73	0.09	1.69	84.79	0.82
Intention to Adopt as a Decision Aid	3	4.10	0.05	1.73	80.94	0.88
Intention to Trust Product Recommendation	3	3.89	0.00	1.63	89.85	0.94

In addition, we surveyed the participants' personality traits in terms of their propensity to trust technology, objects, and others, and the existence of any VA anxiety. Along with participant demographics such as age, gender, nationality, mother tongue, product category knowledge, VA usage and ownership, and satisfaction with past voice experience. Additional measures were also collected from the log data of the Alexa app for control purposes.

5.2 Measurement Invariance (MI)

The invariance test shows the consistency of the relationship between items and their underlying construct across groups (Steenkamp & Baumgartner, 1998). Constraints were assigned to groups to determine if there was equivalence across groups at both the measurement and structural levels. We examined the MI of the model measure across VA empathy groups first and buyer-type groups later; results are shown in Table 6. For the group standard versus empathic VA level, the difference in the CFI value between the configural model and the constrained model is small (less than 0.01) and non-significant (p >.05). For the group individual versus family buyer, we could not interpret the results of the χ^2 difference test comparing the models featuring scalar invariance and configural invariance due to negative test results. Thus, we performed the Wald test of parameter constraints to validate the model fit invariance, Wald $\chi^2_{(1)} = 0.554$, $p = 0.457$. Based on the overall fit statistics, the CFI and TLI

difference tests, we conclude that the model measures featured adequate configural, metric, and scalar invariance (Cheung & Rensvold, 2002; Steenkamp & Baumgartner, 1998). Accordingly, we can assume the equivalence of loadings, intercepts, and residuals across groups.

Table 6. Model Fit Test Statistics, Fit Indices, and Changes for the MI Analyses.

	Model fit test statistics and fit indices						**Change**			
	χ^2	*df*	*CFI*	*TLI*	*RMSEA*	*SRMR*	*χ^2 diff*	*df diff*	*CFI diff*	*TLI diff*
VA empathy										
1. Configural Invariance	810.63	610	0.974	0.968	0.041	0.037	-	-	-	-
2. Metric Invariance	823.51	628	0.975	0.970	0.040	0.039	12.88	18	0.001	0.002
3. Scalar Invariance	845.68	646	0.974	0.970	0.040	0.040	35.05	36	<0.001	0.002
Buyer type										
1. Configural Invariance	845.18	610	0.971	0.963	0.045	0.038	-	-	-	-
2. Metric Invariance	872.80	628	0.969	0.963	0.045	0.043	27.62	18	-0.002	<0.001
3. Scalar Invariance	903.15	646	0.968	0.962	0.046	0.043	57.97*	36	-0.003	-0.001

*Denotes the negative test statistic cannot be interpreted, and a Wald test of parameter constraints was examined instead.

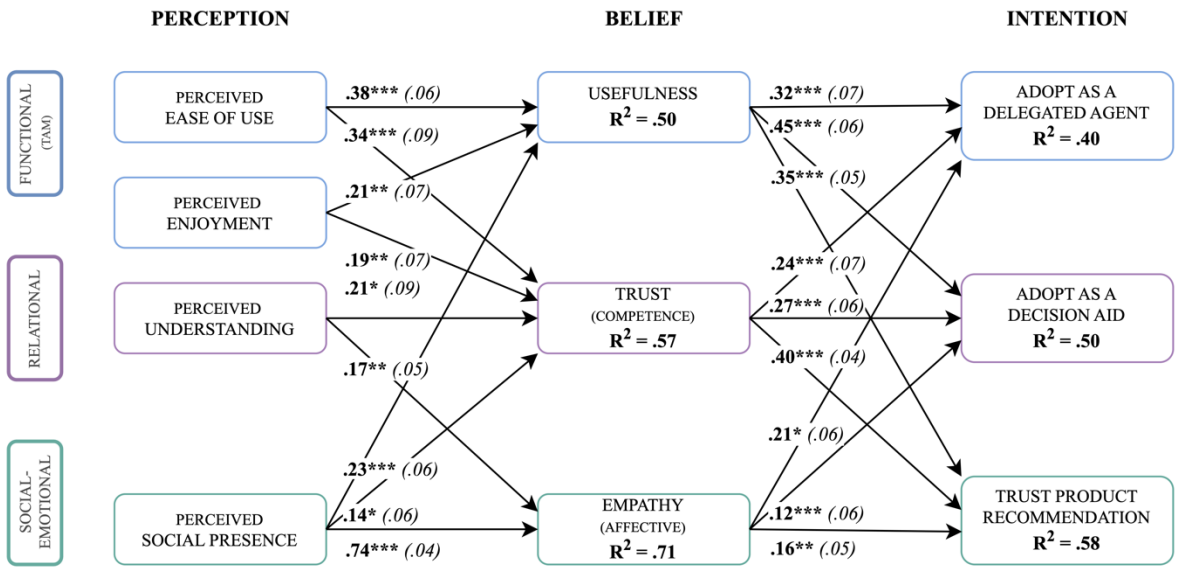
χ^2 diff=χ^2 difference test; df diff=degrees of freedom of the χ^2 difference test; CFI diff=comparative fit index difference test; TLI diff=Tucker-Lewis index difference test.

6. Results

6.1 Structural Model Estimation

The structural equation model, estimated based on the hypothesized model, outlined goodness of fit ($\chi^2_{(323)} = 475.75$, $p \approx .00$, RMSEA = .03, SRMR = .03, CFI = .98, and TLI = .98). Results in Figure 2 reveal that the influence of ease of use on usefulness (β = .38, s.e. = .06) and trusting competence (β = .34, s.e. = .09) is strong and positive, in support of H1a and H1b, respectively. We found that enjoyment positively impacts both usefulness (β = .21, s.e. = .07) and trusting competence (β = .19, s.e. = .07), in line with H2a and H2b. As predicted in H3a and H3b, sense of understanding has a positive and strong effect on trust competence (β = .21, s.e. = .09) and affective empathy (β = .17, s.e. = .05). Furthermore, social presence influences the beliefs of usefulness (β = .23, s.e. = .06), trusting competence (β = .14, s.e. = .06) and affective empathy (β = .74, s.e. = .04), in support of H4a, H4b and H4c, respectively.

Figure 2. Estimated Model.



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

Note: Coefficients are standardized; standard errors are in parentheses.

Antecedents explain 50% of the variance in usefulness beliefs, 57% of the variance in trusting competence beliefs and 71% of the variance in affective empathy beliefs. The impact of usefulness, trusting competence and empathy on the dependent variables is significant and positive. As expected, usefulness influences the intention to adopt the VA as a delegated agent (β = .32, s.e. = .07), adopt the VA as a decision aid (β = .45, s.e. = .06) and trust VA's product recommendations (β = .35, s.e. = .05). Thus, H5a, H5b and H5c are supported. Moreover, we found that the trust competence impacts the behavioral intention to adopt as a delegated agent (β = .24, s.e. = .07), adopt as a decision aid (β = .27, s.e. = .06) and trust product recommendation (β = .40, s.e. = .04), in support of H6a, H6b and H6c. Lastly, empathy influences the intention to adopt as a delegated agent (β = .21, s.e. = .06), adopt as a decision aid (β = .12, s.e. = .06) and trust product recommendation (β = .16, s.e. = .05). Thus, H7a, H7b and H7c receive support. The percentages of variance in adopt as a delegated agent, adopt as a decision aid, and trust product recommendation, as explained by their antecedents, were 40%, 50%, and 58%, respectively. Hence, hypotheses H1-H7 are supported.

6.2 Moderation and Interaction Effects

We test the moderation hypothesis M1 using the subsample *VA empathy level* (high vs. standard), the moderation hypothesis M2 using the subsample *buyer type* (family vs. individual) and the interaction effect using the total sample consisting of the subsamples *VA empathy level* and *buyer type*.

Manipulation Check. A one-way analysis of variance (ANOVA) was conducted to compare VA's empathic score of "Overall, I think Alexa is empathic" in the standard ($M_{standard}$ = 2.71, SD = 1.50) and high empathy groups (M_{high} = 3.47, SD = 1.70). The difference in scores between the two groups was significantly different from zero at the 95% confidence interval (F[1,384] = 21.462, p < .000). Participants in the high empathy group have firmer empathy beliefs towards VAs than those in the standard empathy group. Thus, we conclude that VA empathy level manipulation was successful.

6.2.1 Mean Comparison

In order to examine possible differences in the postulated relationships across the scenarios of voice shopping when using a standard Alexa (with standard shopping flow and framing) versus a relatively more empathic Alexa, we performed a two-sample t-test on all theoretically relevant variables. In Table 7, the user of the empathic Alexa version shows higher scores for all ten constructs when compared to standard Alexa users. All differences in factor means are significant at the 95% confidence interval with the exception of intention to adopt as a delegated agent (t[384] = 1.80, p = .071) and decision aid (t[384] = 1.89, p = .059), only showing a tendency towards significance. Thus, the hypothesis of moderation (M1) is generally confirmed.

Table 7. Test of Factor Mean Differences Between Subsamples.

Standard/Empathic Alexa User	**Standard Factor Mean**	**Empathic Factor Mean**	**t-Value, p-Value**
Perceived Ease of Use	0	.21	1.95, p = .05
Perceived Enjoyment	0	.23	2.15, p < .05
Perceived Sense of Understanding	0	.22	1.97, p < .05
Perceived Social Presence	0	.43	4.02, p < .001
Usefulness	0	.27	2.66, p <.01
Trust (Competence)	0	.29	2.57, p = .01
Empathy (Affective)	0	.50	4.73, p < .001
Intention to Adopt as a Delegated Agent	0	.20	1.80, p = .071 (n.s.)
Intention to Adopt as a Decision Aid	0	.20	1.89, P = .059 (n.s.)
Intention to Trust Product Recommendation	0	.28	2.72, p <.01

Individual/Family Buyer	**Individual Factor Mean**	**Family Factor Mean**	**t-Value, p-Value**
Perceived Ease of Use	0	-.01	-.12, n.s.
Perceived Enjoyment	0	-.07	-.67, n.s.
Perceived Sense of Understanding	0	-.19	-1.66, n.s.
Perceived Social Presence	0	.12	1.10, n.s.
Usefulness	0	.35	3.04, p < .01
Trust (Competence)	0	-.03	-.27, n.s.
Empathy (Affective)	0	.12	1.08, n.s.
Intention to Adopt as a Delegate Agent	0	-.05	-.43, n.s.
Intention to Adopt as a Decision Aid	0	.10	.91, n.s.
Intention to Trust Product Recommendation	0	.15	1.34, n.s.

The lower panel of Table 7 shows the differences in the factor means between the groups of family and individual (buyer type) and their significance level. A two-sample t-test showed that theoretically relevant variables do not statistically differ when study participants shop on Alexa with other family members rather than individually. All differences in factor means are non-significant at the 95% confidence interval except usefulness ($t[384] = 3.04$, $p < .01$), showing a significant difference between the two subsamples. Overall, we can infer that empathic VAs influence consumers' responses to VAs, and these factors remain unchanged regardless of the social shopping context: individual vs. family decision-making. Hence, the moderation hypothesis M2 is generally supported.

6.2.2 Interaction Between the Effects of VA Empathic Level and Buyer Type

After conducting the necessary assumption tests, a two-way ANOVA revealed a statistically significant interaction between the effects of VA empathy level (high vs. standard) and buyer type (family vs. individual) on:

Perceived Ease of Use (F[1, 382] = 9.44, p < .01). Simple main effects analysis showed a nonsignificant effect of the buyer type (M_{family} = 4.82, $M_{individual}$ = 4.84; F[1, 382] = .02, p = .889) and a nonsignificant effect of VA empathy level (M_{high} = 4.93, $M_{standard}$ = 4.73; F[1, 382] = 2.24, p = .135).

Perceived Enjoyment (F[1, 382] = 9.44, p < .01). Simple main effects analysis showed a nonsignificant effect of the buyer type (M_{family} = 4.51, $M_{individual}$ = 4.66; F[1, 382] = .79, p = .376) and a nonsignificant effect of VA empathy level (M_{high} = 4.70, $M_{standard}$ = 4.47; F[1, 382] = 1.87, p = .172).

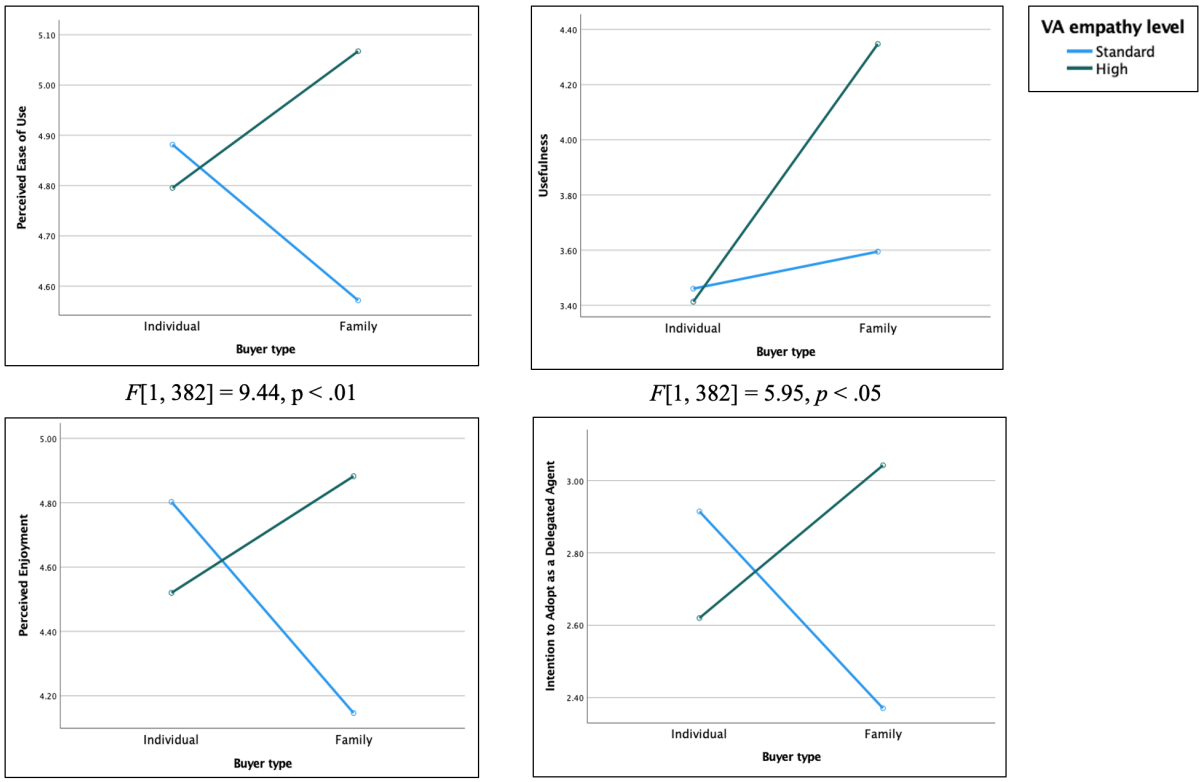
Usefulness (F[1, 382] = 5.95, p < .05). Simple main effects analysis showed a significant main effect of the buyer type (M_{family} = 3.97, $M_{individual}$ = 3.44; F[1, 382] = 10.63, p < .01) and a nonsignificant main effect of VA empathy level (M_{high} = 3.88, $M_{standard}$ = 3.53; F[1, 382] = 4.63, p < .05).

Intention to Adopt as a Delegated Agent (F[1, 382] = 9.04, p < .01). Simple main effects analysis showed a nonsignificant effect of the buyer type (M_{family} = 2.71, $M_{individual}$ = 2.77; F[1, 382] = .14, p = .705) and a nonsignificant effect of VA empathy level (M_{high} = 2.83, $M_{standard}$ = 2.63; F[1, 382] = 1.38, p = .241).

A 2 x 2 ANOVA on the remaining key relational and social-emotional constructs does not present any significant interaction between the effects of buyer and VA empathy levels. Thus, we refrain from reporting the interaction results.

We show statistically significant interaction between the effects of the model moderators only about functional VA elements, including perceived ease of use, perceived enjoyment, usefulness, and intention to adopt as a delegated agent (Figure 3). Concurrently, relational and social-emotional elements of VAs are only characterized by the simple main effect of VA empathy level.

Figure 3. Interaction effect of moderators on perceived VA functional variables.



$F[1, 382] = 9.44$, $p < .01$ $F[1, 382] = 5.95$, $p < .05$

$F[1, 382] = 9.44$, $p < .01$ $F[1, 382] = 9.04$, $p < .01$

Adopting the increasingly relevant social level perspective (Bagozzi & Dholakia, 2002), we consider family shopping as a way for the group members to discuss similar interests while telling jokes or sharing opinions, evaluate products together, and collectively make decisions. Thus, shopping while bonding and socializing generate social benefits from strengthening social relationships (Arnold & Reynolds, 2003). In the collaborative shopping process, group members intend to collaborate (Bagozzi & Dholakia, 2002). Specifically, when a family gathers around a VA to shop for products, the context is inherently socially driven. The family members may have consciously or unconsciously decided to engage in a "social voice experience" where bonding and socializing are preferred to effectiveness and convenience. Thus, in family (vs. individual) shopping, social-hedonic shopping motives (vs. utilitarian) are predominant, as emerged from our results. As such, family buyers using an empathic Alexa display significantly higher scores for perceived functional VA characteristics than family buyers shopping using a standard Alexa. Conversely, individual buyers using a classic Alexa for purchasing show a higher score for functional VA attributes than individuals shopping using an empathic Alexa.

7. General Discussion and Implications

7.1 Theoretical implications

Shopping is a social activity where consumers often demonstrate a tendency to be influenced by their social interactions with other humans and automated machines (Algesheimer et al., 2005; Candrian & Scherer, 2022). We demonstrate that research on human-VA interaction that ignores the effect of empathy and its social-emotional determinants on future behavioral intentions is likely to generate biased results. The study of humans' empathetic reactions toward social bots mainly aims at developing better empathic agents (Carolus et al., 2021). Following a different approach, this research simulates an agent's empathic behavior to foster a consumer's affective response towards that empathic agent (von der Pütten et al., 2020). In particular, we respond to the call to study how VAs influence consumer shopping decisions depending on VA empathic levels and social context applications.

Our study contributes to existing research in several ways. First, findings empirically validate and extend the sRAM framework untangling relationships among perceptions, beliefs, and behavioral intentions across functional, relational, and social-emotional drivers of adoptions. Thus, we confirm that consumer acceptance of VAs depends on their functional performance and ability to fulfill relational and social-emotional needs. At the same time, we theorize the role of affective empathy in the context of AI-based consumer technologies, and we reveal its fundamental mediating role and effect on critical decision-making outcomes. Second, we demonstrate stronger user perceptions, beliefs, and behavioral intention when Alexa shows empathic abilities. Thus, we disclose the strategic role of empathy-related features building on warmth and sympathy in driving the adoption of voice-based agents.

Third, we demonstrate that positive consumers' responses to empathic in-home and embodied AI-based VAs (Amazon Alexa) hold constant in social settings. Thus, we prove shoppers' responses are higher with empathic VAs than when using standard one across individual and collective decision-making settings. We believe the ripple effect paradigm can help us interpret this result. Finally, our findings show an interaction between the effects of buyer type and VA empathy level only on the user's functional TAM-related responses to VAs. Thus, family buyers using an empathic (vs. standard) Alexa display significantly higher scores for functional VA characteristics, while individual buyers show a higher score using a standard (vs. empathic) Alexa. Precisely, the individual shopper displays a stronger task orientation towards performance in efficiency and convenience. Hence, functional benefits play a higher role than

relational and social-emotional benefits in individual shopping and decision-making. In this context, individual shoppers show a reduced focus on the empathic characteristics of the VA, with a negative effect on their willingness to engage in "inefficient" social activity.

On the other hand, in collective shopping within a family, individuals pay greater attention to the empathic abilities of the VA as their experience unfolds in a social context. Family shoppers get together to solve a task. As such, they carry a stronger predisposition to engage at an affective level with the empathic Alexa in that specific moment. These results challenge the assumption that consumers are indiscriminately willing to adapt to the social status of the agent without effect on their perceptions, beliefs, and attitudes.

These results advance understanding of consumer acceptance of AI-based recommendation agents in the discipline of HCI (McLean & Osei-Frimpong, 2019; Pitardi & Marriott, 2021) and service management (Fernandes & Oliveira, 2021; Wirtz et al., 2018). Furthermore, we contribute to the literature addressing consumer-machine relationship formation (van Doorn et al., 2017; Huang & Rust, 2021) within the context of voice commerce (Canziani & MacSween, 2021; Rhee & Choi, 2020), also in family shopping settings (Wald et al., 2022; Ostrowski et al., 2022).

Methodologically, this is the first study employing a *machine behavior* perspective to develop an ad-hoc shopping app to increase the study's ecological validity, thus enhancing it. In doing so, we isolated the effect of VA empathy level in a controlled but realistic purchase environment. Such findings should not be taken as a definitive conclusion but rather as a preliminary result that triggers further studies following the same methodology.

7.2 Implications for managers and policymakers

We expect companies to generate a competitive advantage on voice platforms when they provide expected, still operationally delightful, emotional experiences by understanding consumers' individual and collective emotional states. Without a deep understanding of the managerial implications that the new generation of AI-powered VAs bring from human-computer design, marketing, and commerce, managers may miss the opportunity to create more ethically driven voice shopping experiences for the new class of buyers. The proposed model can guide firms in designing effective shopping-related VAs through third-party applications or owned devices. This study advances that empathic VAs strongly influence the shoppers' experience; however, decision-making outcomes may differ depending on the social context in

which the shopping process occurs. Thus, we suggest managers make the following considerations.

First, experience designers need to find a way to control and manage the level of empathy of the VAs, together with other known functional and relational variables affecting consumer decisions. This study shows that higher empathy can be achieved through empathic responses, listening, and feedback with moderate conversational design efforts. Through test and trial phases, managers may design an agent going beyond the standard VA capabilities, for instance, customizing *brand voice* and *tone of voice* to enrich voice experiences emotionally.

Second, although prior research generally suggests that providing AI-based agents with human-like features could enhance consumers' positive responses, the current study indicates that adopting a shopping-related VA with empathic characteristics may be a backlash. Specifically, we present the negative effect of providing hedonic experiences to task-oriented users (generally, single shoppers) and utilitarian experiences to those with social motives (families). As such, the decision to enhance the empathic characteristics of shopping-related VAs needs to consider the social context in which the voice-enabled experience takes place.

Finally, companies targeting families involved in social voice shopping may assume that the positive affective responses to empathic VAs are extended to all interlocutors during low-involvement category shopping sessions. Advancements in conversational technologies are expected to enable effective simultaneous multiparty interaction with VAs. To timely exploit social influence dynamics while gaining a better understanding of the preferences and behaviors of different family members, firms need to monitor VA technology advancements and create strong partnerships with VA manufacturers. Nevertheless, creating ethically driven services requires managers to explore how voice interaction data is captured and used in training AI models characterized by empathic features.

Since consumers may be more susceptible to empathic VA influence, active regulatory requirements about fairness and transparency may become increasingly necessary. Thus, we suggest policymakers make the following considerations.

The evolution towards more empathic VAs may offer a better shopping experience for the consumers they are assisting; thus, it is not inherently negative. However, a potential issue arises when subtle nudging techniques are used as means to influence shopping decisions. With an objective difficulty in assessing the persuasive effect of ongoingly evolving social VAs,

policymakers could primarily focus on increasing accountability and transparency of the product recommendation rather than understanding the emphatic nuances of the machine.

Consumer protection could be achieved with the introduction of policy and legal frameworks that consider VAs as agents with legal obligations to fairly consider the interests of the consumer ahead of those of the VA manufacturer and its technology partners. Because the interests of multiple actors need to co-exist in the VA ecosystem, it is particularly tedious to guarantee that, regardless of the empathy characterization of the VA and the interaction content, consumers are not nudged to purchase undesired and unnecessary products with a negative effect on their well-being. However, a standard rule that seeks accountability for any risk of exploitation in consumers could be applied to the owners of voice-based services.

Concurrently, service providers could be asked to disclose the criteria used in formulating product recommendation rankings. As such, different forms of explainable AI could support the consumer in understanding what type of information to be delivered by the VA to trust and when information asymmetries exist.

The increased regulation framework might prevent loss in consumer decision autonomy when AI-based agents become influential enough to be considered delegated partners responsible for fulfilling shopping tasks on the consumers' behalf.

7.3 Limitations and Future Studies

Several limitations of the proposed study should be recognized. First, this research was conducted within the context of first-time VA usage in general and in voice commerce. Thus, given this perspective, it was not possible to consider the effect of empathy during the development of the human-VA relationship. For instance, it is still being determined whether the generally positive impact of empathy fades when VA usage increases, such as when consumers become familiar with the empathic response schema. Thus, future empirical investigations should employ a longitudinal design to explore how empathy beliefs evolve. Second, participants were asked to purchase low-involvement products with relatively low combined economic value ($10.00 - $15.00). Although this scenario reflects the current basket size in voice commerce purchases, we expect social influence dynamics within the family context to play a more relevant role when high-involvement product categories are purchased using VAs. As such, future studies can consider individual and collective shopping behavior with both low- and high-involvement purchases. Third, the authors artificially defined the two

product categories for sale on Alexa. Besides limiting the generalizability of the findings, imposing the type of product to purchase on the participants may affect their motivation and emotional state. Future studies could offer the user the possibility of purchasing a broader range of products and making decisions based on their immediate shopping needs. Lastly, this study uses essential natural language programming tools to enhance the empathic VA characteristics (empathic listening, response, and feedback). However, new affect-driven VA capabilities, such as speaking personas, and voice emotions through intonation, tone, pause, emphasis, or custom brand voices, are becoming available primarily to software developers (and companies) building voice-based experiences. Thus, the future design of custom voice apps for research may include advanced empathic features, potentially generating higher emotional responses in consumers. Overall, future studies on voice commerce should further uncover process mechanisms and identify boundary conditions in different shopping settings.

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Appendix

Appendix 1. Intent, Utterance and Interaction Flow in the Voice Shopping Alexa Skill (Standard vs. Empathic)

Section	**Speaker**	**Interaction content** (*in bold*: content only available in condition "empathic")
1. Service activation	User	Alexa, open '*voice shopping*'!
	Alexa	Before we explore the app, do you mind providing your '*promo code*'?
2. Promo code and welcome message	User	My promo code is *"…"*.
	Alexa	a) **Excellent!** Your promo code is found. **I am happy** we can now start your product search**. A warm welcome to the voice shopping application. I hope you are having a good day and you are safe and healthy;** b) Promo code not found *(back to section 1).*
3. Shopping preference gathering *Note: these preferences are NOT use for following product recommendations*	Alexa	**Before we shop together, I'd like to learn more about your preferences. I will make some statements. Please answer from 1 to 10 the extent to which you agree with each statement. (Please answer one person at a time). Ready?** **Number one: When shopping, I often seek the cheapest available option: "…".** **Number two: When shopping, I often rely on the brand name to choose my option: "…".** **Number three: When shopping, I often care about the ratings and reviews by other users: "…".** **Great! Thanks for sharing your general shopping preferences with me. I now feel confident to recommend you the set of products that best fit your needs.**
	User	*(answer/s provided during the pause "…").*
4. Product search	Alexa	**Let's start shopping!** What would you like to buy?
	User	AA batteries/Pain killer *(or variations)*

5. Product recommendation (not accepted)	Alexa	The top search result for AA batteries is *(brand)* double-A 1.5-volt performance alkaline batteries, pack of 4. It's *(price)* total. Would you like to buy it? - or - The top search result for Pain killer is *(brand)* extra strength pain reliever and fever reducer, paracetamol tablets 500 mg, 20 pieces. It's *(price)* total. Would you like to buy it?
	User	a) Yes *(go to section 9)*; b) No.
	Alexa	I also found *(brand)* double-A 1.5-volt performance alkaline batteries, pack of 4. It's *(price)* total. Would you like to buy it? - or - I also found *(brand)* extra strength pain reliever and fever reducer, paracetamol tablets 500 mg, 20 pieces. It's *(price)* total. Would you like to buy it?
6. Suggestion pause process or repeat options	Alexa	*(After the third rejected recommendation)* That's all I have for now. If you would like to pause the purchasing process, say, 'Give me more time'. If you want to listen to the options again, say, 'Repeat my/our options'. How would you like to proceed?
7a. Pause process	User	Alexa, give me/us more time!
	Alexa	Sure! I will now play some music. When you are ready to make your choice, say, 'I am/we are ready'. **Just as a hint: If you have any doubt, you can ask me 'what's the cheapest option?' or 'what's the best brand?' or 'give me more info!'.**
7b. Repeat options	User	Alexa, repeat my/our options!
	Alexa	Great! Say option one for *(product description)*, option two for *(product description)*, option three for *(product description)*, option four for 'none of the above'. Which option or brand would you like to buy?
	User	Brand name – or – Option number
8. Feedback and satisfaction verification	Alexa	**That's a great choice! Ratings and reviews for this product are excellent for** *(description)*. It's *(price)*. **I am sure you will be fully satisfied with it.** Do you want me to complete the order of this item? **Are you happy with your decision?**
	User	a) Yes; b) No *(back to section 6)*.
9. Order confirmation and closing message	Alexa	Your order will be shipped to your default address today. **I am very happy we found a product for you. In case you need further assistance, do not hesitate to ask.** Thank you **for your trust** and goodbye!