Journal of Retailing 100 (2024) 293–315

Contents lists available at ScienceDirect

Journal of Retailing

journal homepage: www.elsevier.com/locate/jretai

Facilitating retail customers' use of AI-based virtual assistants: A meta-analysis

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ARTICLE INFO

Article history:
Available online 13 May 2024

Associate Editor: Jenny van Doorn

Keywords:
Meta-analysis
Artificial intelligence
Virtual assistants
Retail technologies

ABSTRACT

Retailers rely on virtual assistants (VAs), such as Amazon's Alexa and chatbots, to deliver 24/7 customer service at low costs, as well as novel shopping opportunities. Despite improved VA capabilities due to artificial intelligence (AI), many retailers still struggle to convince customers to become repeat users of VAs. Therefore, to establish recommendations for how to facilitate VA use, this meta-analysis extracts 2,766 correlations from 244 independent samples of customers interacting with VAs. The results suggest that customer-, VA-, and shopping occasion–related factors all influence technology use. Price value is the strongest driver, followed by support, social influence, and anthropomorphism. Performance risk, competence, and trust matter to lesser extents. These factors exert strong indirect effects by triggering two customer responses: cognitive and emotional. Negative emotions emerge as a particularly important mediator. Finally, several VA types enhance or weaken the noted effects, including whether they are intelligent/less intelligent, commercial/noncommercial, voice-/text-based, and avatar-/non-avatar-based. The results suggest no one-size-fits-all approach applies for VAs, because their performance varies across customer responses. The current meta-analysis provides in-depth guidance for retailers seeking to select appealing VAs.

Retailers' virtual assistants (VAs), such as Amazon's Alexa or IKEA's chatbot Billie, provide customer service and shopping opportunities (Guha et al. 2021), by engaging virtually in customer conversations and actively guiding purchase decisions (Dellaert et al. 2020). In addition to emulating human intelligence, they can communicate through text (chatbot) or voice (voice assistant) and facilitate technical support, online shopping, and consistent customer service to myriad customers at low costs (Shankar 2018). For example, the beauty retailer Sephora's chatbot greets customers formally and provides them with several service options, ranging from skincare advice to booking a makeover (CBInsights 2021). Customers have embraced and engaged with the VA, sending it daily messages (Indigo9 2023). However, in other cases, VAs have failed to achieve acceptance; the chatbot available through 1–800 Flowers, a floral and gift retailer (Digiday 2023), presents what customers describe as a multiple-choice test and limits them from performing "off-script" tasks, such as changing the delivery date. More broadly, only 8% of customers used chatbots during a recent customer service experience, and only 25% of those people would use that same chatbot again in the future (Gartner 2023).

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https://doi.org/10.1016/j.jretai.2024.04.001

Still, advances in artificial intelligence (AI) and the advent of ChatGPT continue to prime retailers' interest in VAs, in search of benefits like the potential to reduce labor costs by an estimated $80 billion (Digiday 2022). Therefore, retail managers need to understand when and why customers willingly use VAs. Prior literature cites some such factors, related to the customer, VA, and shopping occasion, often in accordance with the unified theory of acceptance and use of technology (e.g., social influence; Venkatesh et al. 2012) and its extensions (e.g., trust; Blut et al. 2022). The research field remains fragmented though, characterized by inconsistencies and knowledge gaps, and as it expands, we observe increasing contradictions among the empirical findings. For example, some studies assert that retailers' support influences technology use (Kuberkar and Singhal 2020), but others dismiss this antecedent as less relevant (Dogra and Kaushal 2021). Such contrasts indicate the need for a meta-analysis that synthesizes the varied empirical evidence and that thus can provide retail managers with clearer guidance.

Notably, many scholars investigating the processes through which various factors influence VA use build on the cognition-based technology acceptance model (TAM; Venkatesh and Bala 2008), according to which the antecedents exert indirect effects on technology use through two cognitive responses: ease of use and usefulness perceptions. Yet studying solely cognitive responses may not be sufficient (Bagozzi et al. 2022). Considering the expanding capabilities of VAs, customers' emotional responses to them might function as mediators of technology use too (Huang and Rust 2021). When advanced VAs leverage AI and natural language processing to detect customer sentiment and respond accordingly with human-like tones and empathy, customers likely experience emotional reactions (Huang and Rust 2021). The lack of explicit investigations of customers' emotional responses to VAs[1] thus leaves unclear which customer characteristics, VA perceptions, and shopping occasion perceptions trigger different customer responses. The antecedents of customer cognitions and emotions might differ, and cognitive or emotional responses could function as more or less important mediators between antecedents and use, for example.

In their efforts to ensure continued technology use, retailers thus must identify which VA types influence (1) the impacts of different antecedents on customer cognitions and emotions and (2) the impacts of these cognitions and emotions on technology use. When retail managers plan to implement a VA, they likely make strategic design decisions about the type of VA to develop, which might be classified by the intelligence of VA, its focal task, its communication modality, and avatar use. In detail, should the VA's intelligence be based on simple, cost-effective, preprogrammed scripts, or should it reflect highly sophisticated programming, which also might trigger AI anxiety in customers (Li and Huang 2020)? Different VAs also might be assigned tasks devoted to the sale of specific products, such that it requires integration with inventory management systems, or else be employed in consultative roles and offer connections to other applications. Another basic decision involves communication modality: Text-based VA is simpler to implement but requires customer literacy; voice communication can transmit diverse informational cues (CBInsights 2021). Finally, the VA might have its own avatar, which can be portrayed as an independent character and give the customer a vivid impression of an interaction partner, whereas the absence of an avatar allows for more possibilities for projection and imagination. Because most studies examine single VAs, we lack comparative insights into the performance of different VA types and their influences.

In an attempt to move the VA field forward and address these issues, we conduct a meta-analysis of empirical results involving 244 independent samples, reported in 195 studies. The meta-analytic framework identifies three groups of antecedents of customer cognitions and emotions: customer characteristics, VA perceptions, and shopping occasion perceptions. The effects of both cognitions and emotions appear as mediators between these antecedents and the use of VA technology. We also include potential moderating effects of the different VA types: intelligent versus less intelligent, commercial versus noncommercial, voice- versus text-based, and avatar- versus non-avatar-based. On the basis of this framework, our meta-analysis clarifies the importance of different antecedents for explaining VA use; specifies the roles of cognitive and emotional responses, elicited by the different antecedents, for influencing VA use; and defines which VA types influence both the impacts of different antecedents on customer cognitions and emotions and the impacts of these cognitions and emotions on technology use. In turn, retail managers can use this framework to guide their efforts to encourage customers' increased use of helpful VAs.

The implications of this meta-analysis for managers pertain to the factors that prompt customers use VAs, triggered cognitive and emotional responses, and VA type selection. In terms of key influences, managers should note the relevance of different customer characteristics, VA perceptions, and shopping occasion perceptions. Price value and support exert the largest total effects, followed by social influence, anthropomorphism, performance risk, trust, and competence. Even if all antecedents matter, retailers should allocate their financial budgets in accordance with our findings. Beyond customers' cognitive judgments, managers need to acknowledge the positive and negative emotions that customers experience during interactions with VAs, as represented in our conceptual framework. Finally, when selecting a VA to introduce, managers can leverage the effects of different acceptance drivers. There is no one-size fits-all approach; VAs' performance inevitably varies across customer responses. We detail which VAs we recommend for enhancing which customer responses and then translating them into use. For example, to intensify the effects of antecedents on ease-of-use perceptions, retailers should select intelligent VAs for noncommercial tasks, with text-based communication and avatars. Managers interested in translating cognitions and emotions into increased technology use should select rather simple VAs for noncommercial tasks, relying on voice-based communication and avoiding avatars.

[1] Some meta-analyses of related technologies adopt different foci, as we detail in Web Appendix A.

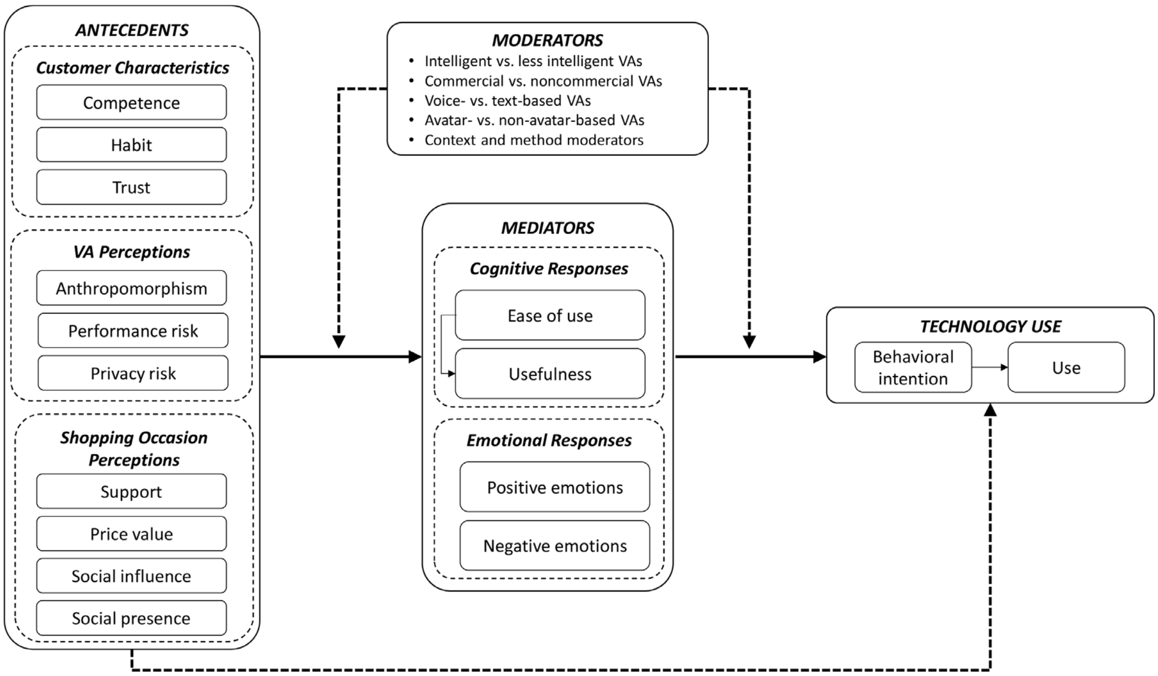

Fig. 1. Meta-analytic framework of factors influencing VA use.

1. Meta-analytic framework

Fig. 1 depicts the conceptual framework, which comprises three groups of variables that influence technology use: (1) customer characteristics, VA perceptions, and shopping occasion perceptions as antecedents; (2) cognitive and emotional responses as mediators; and (3) moderators. Table 1 provides definitions of all the constructs.

First, pertaining to the antecedents of technology use in our conceptual model, information systems literature frequently cites person–environment fit theory to explain that customer responses to technology depend on customer characteristics but also environmental factors related to the technology and situation in which the technology is being used (Ayyagari et al. 2011). Accordingly, we differentiate customer characteristics (competence, habit, trust), VA perceptions (anthropomorphism, performance risk, privacy risk), and shopping occasion perceptions (available support, price value, susceptibility to social influence, perceived social presence).[2] According to the unified theory of acceptance and use of technology, several of these antecedents should relate directly to technology use (e.g., habit, support, price value, social influence; Venkatesh et al. 2012). Other studies identify other relevant antecedents (e.g., competence, trust, anthropomorphism; Blut et al. 2022), which have been studied widely. Accordingly, we do not discuss them in detail and instead refer to relevant literature that covers these topics effectively (Blut et al. 2022; Venkatesh et al. 2012). Also, because we suspect strong indirect effects of these antecedents through mediators, we do not discuss the direct effects of antecedents on technology use in detail.

Second, the framework contains two sets of parallel mediators: cognitive and emotional responses. Testing indirect effects through mediators helps clarify why different antecedents might affect technology use, while also allowing for more accurate assessments of the importance of each antecedent (Grewal et al. 2018). As we noted, prior literature predominantly relies on cognition-based models (Venkatesh and Bala 2008), indicating the need for more studies of customer emotions (Huang and Rust 2022). Bagozzi, Brady, and Huang (2022, p. 499) elaborate: “Early research into the adoption of technologies focused on the functional benefits of technology… As research and knowledge progressed…, we came to the recognition that emotional processes can be important in decision-making.” Therefore, we consider two parallel response paths, which reflect Mischel and Shoda’s (1995) description of the cognitive–affective processing systems. According to this model, people tend to concentrate selectively on various situational aspects, then mentally and emotionally categorize and encode them. Mischel and Shoda (1995) stress that resultant behaviors are influenced by both characteristics of the situation and the arrangement of the individual cognitive and emotional network that has been triggered. That is, we integrate insights from the TAM and its prediction of cognitive responses (ease of use, usefulness) as mediators (Venkatesh and Bala 2008) with

[2] Initially, Short et al. (1976) compared different communication media when developing social presence theory and understood social presence as “a quality of the medium itself” (p. 65). Later, scholars extended this technologically deterministic perspective, by stressing that social presence varies across contexts and situations in which the communication occurs (Kreijns et al. 2022). Thus, we classify this antecedent as shopping occasion perception.

Table 1
Construct definitions, aliases, and representative studies.

Construct	Definition	Common Aliases
Antecedents		
Customer Characteristics		
Competence	Customer's potential to fully utilize information and communication technology to improve their performance of specific job tasks (Blut et al. 2021).	Expertise, self-efficacy, prior use experience
Habit	The extent to which people tend to perform a behavior automatically because of learning (Venkatesh et al. 2012).	–
Trust	Psychological expectation that others will keep promises and will not behave opportunistically in expectation of a promised service (Blut et al. 2021).	Distrust (r), credibility, sincerity
VA Perceptions		
Anthropomorphism	Attribution of human characteristics or traits to nonhuman agents (Epley et al. 2007).	Perceived humanness, authenticity of conversation
Performance risk	The loss incurred when a service does not perform as expected (Tam, 2012).	–
Privacy risk	Potential loss of control over personal information, such as when information about customers is used without their knowledge or permission (Featherman and Pavlou 2003).	Privacy concerns, security concerns
Shopping Occasion Perceptions		
Support	A user's perceptions of the resources and assistance available to perform a behavior (Venkatesh et al. 2003).	–
Price value	The individual's cognitive tradeoff between the perceived benefits of an application and the monetary cost of using it (Dodds et al. 1991).	Perceived value, benefits
Social influence	The degree to which the user perceives that important others believe they should use the technology (Venkatesh et al. 2003).	Subjective norm, interpersonal influence
Social presence	Perception to which a customer believes that someone is really present (Heerink et al. 2008), e.g. during a shopping encounter it varies across contexts and situations in which customers communicate with the VA (Kreijns et al. 2022).	–
Cognitive responses		
Ease of use	The degree to which a user will find the use of a technology to be free from effort (Davis et al. 1989).	Effort expectancy
Usefulness	The subjective probability that using a technology will improve the way a user completes a given task (Davis et al. 1989).	Performance expectancy, helpfulness
Emotional responses		
Positive emotions	Intense positive feelings directed at someone or something (Fishbach and Labroo 2007).	Enjoyment, likability, pleasure, warmth perception
Negative emotions	Intense negative feelings directed at someone or something (Fishbach and Labroo 2007).	Discomfort, anxiety, feeling uncomfortable
Technology use		
Behavioral intention	The strength of one's intention to perform a specified behavior (Fishbein and Ajzen, 1975).	Intention to use, willingness to use, adoption intention
Use	Actual system use in the context of technology acceptance (Davis, 1989).	Actual acceptance, actual adoption, actual use, usage behavior
Moderators		
Intelligent vs. less intelligent VAs	Refers to the VA's ability to learn, reason, and problem-solve (Blut et al. 2021).	Dummy-coded whether the study examines VAs that are intelligent (1) or less intelligent (0).
Commercial vs. noncommercial VAs	Refers to the commercial (e.g., e-commerce) and noncommercial (e.g., fashion advice, information service) tasks that VAs are employed for (Blut et al. 2016).	Dummy-coded whether the study examines VAs that provide commercial (1) or noncommercial (0) services
Voice-based vs. text-based VAs	Refers to the mode of communication used by the VA: voice (e.g., Siri, Alexa) or text (e.g., Replika, Facebook chatbots) (Rzepka et al. 2022).	Dummy-coded whether the study examines VAs that rely on voice-based (1) or text-based (0) communication.
Avatar-based vs. non-avatar-based VAs	Refers to generic graphic representations of the VA personified by means of computer technology (Holzwarth et al. 2006).	Dummy-coded whether the study examines VAs that use an avatar (1) or do not use an avatar (0).

environmental psychology theories that predict mediation by emotions (positive and negative) of the effects of different antecedents on technology use (Mehrabian and Russell 1974).

Third, as moderators, we assess which VA types enhance or weaken (1) the effects of different antecedents on customer cognitions and emotions and then (2) the effects of these cognitions and emotions on technology use. The moderators thus reflect the differences that characterize major VA types: intelligent versus less intelligent, commercial versus noncommercial, voice- versus text-based, and avatar- versus non-avatar-based. In this sense, moderators, as manifested by the VA types, differ explicitly from the antecedents in our model. The antecedents pertain to consumers' subjective perceptions (e.g., VA perceptions), but the VA types refer to technology groups with similar, objectively distinguishable features (Lee et al. 2003). Such types often appear as potential moderators in TAM, due to their influence on the effects of different perceptions

(Venkatesh et al. 2016). For example, Lee et al. (2003) classify information systems into four categories (i.e., communication, general-purpose, office, and specialized business systems) and propose that these categories exert moderating influences in the TAM. Similarly, we propose a classification of different VA types and assess their potential moderating influences. In line with context-specific theorizing in information systems research, we regard technology types as contextual factors that inform the relevance of customer characteristics, technology perceptions, and situational factors (Hong et al. 2014). Venkatesh et al. (2016) argue explicitly that the technology type is a dimension of the context that interacts with different antecedents, such as support and social influence, as well as with cognitive responses like ease of use and usefulness.

1.1. Empirics-First approach

For this meta-analysis, we take an empirics-first approach (Golder et al. 2023). Instead of developing specific hypotheses, we use a comprehensive data set to conduct a meta-analysis of all possible effects in the framework, estimate their effect sizes, and assess moderators. Scholars still engage with the literature throughout the stages of an empirics-first approach. As Golder et al. (2023) explain, "In the first stage, existing theory (or the lack thereof) provides an aptness (suitability) check… In the second stage, priors or hunches that guide EF research stem from the scholar's accumulated experience (including previous exposure to the literature). In the final stage, the literature informs the interpretation of discoveries while the discoveries expand or challenge the literature" (Golder et al. 2023, p. 324). In our research, the emotional response mediators and moderating effects are novel, so they justify the use of an empirics-first approach. Thus, we review literature on these topics to identify gaps or weak empirical evidence, limited guidance, or the existence of unclear, multiple, and conflicting arguments.

1.2. Influence of antecedents on cognitive responses

The influence of antecedents on cognitive responses received significant scholarly attention. Building on the TAM (Venkatesh and Bala 2008), scholars have proposed different antecedents of technology use, linked to ease of use and usefulness perceptions (Web Appendix B). *Ease of use* is the effortlessness with which a user operates a technology (Davis et al. 1989), and perceived *usefulness* (Venkatesh and Davis 2000) is the user's belief that the technology will improve their task performance. Both positively influence technology use (Davis et al. 1989). Turning to *customer characteristics*, competence, habit, and trust relate positively to both ease of use and usefulness. Customers who have developed competence and habitual usage of a VA likely understand its functionalities better and can more accurately evaluate its usefulness (Karahanna and Straub 1999). Trust also enhances usefulness and ease of use perceptions by providing reassurances about the VA's competency and reliability (Mou et al. 2017). Among *VA perceptions*, anthropomorphism might enhance usefulness and ease of use by encouraging customers to interact with a VA whose human-like appearance encourages them to apply familiar social rules to the interaction, discover its benefits, and learn about the technology (Wünderlich and Paluch 2017). In contrast, privacy and performance risks may reduce perceived ease of use by complicating the interaction (Pavlou 2003); they also suggest the potential for malfunction and data insecurity, thereby diminishing usefulness (Hubert et al. 2019). In their *shopping occasion perceptions*, customers perceive VAs as more useful and easier to use if retailers provide support (Laumer et al. 2019; Venkatesh 2000). Furthermore, VAs may appear more useful when the price value is good, because customers infer technology benefits. Positive social influence can enhance usefulness too, in that customers incorporate recommendations by important others into their utility assessments (Venkatesh and Davis 2000) and thus become more inclined to learn to use the VA (Shen et al. 2006). Social presence perceptions during the shopping encounter encourage consumers to learn using the technology and shape their utility perceptions (Pitardi and Marriott 2021).

1.3. Influence of antecedents on emotional responses

The impacts of antecedents on emotional responses are relatively novel. Prior literature provides limited insights regarding the specific mediating effects related to emotional responses, though Huang and Lee (2022) cite environmental psychology and predict that different antecedents affect technology use through both positive and negative emotions (Web Appendix B). *Positive emotions* associated with VAs, like happiness and gratitude, may facilitate technology use, because they foster approach behaviors (Mehrabian and Russell 1974). Regarding *customer characteristics*, competent customers likely derive more pleasure from a product (Clarkson et al. 2013), and customers habituated to VAs may perceive the technology as beneficial to their well-being (Phipps and Ozanne 2017), which may elicit feelings of contentment. Trust, due to its correlation with positive feelings and emotional VA bonding, should influence positive emotions (Johnson and Grayson 2005). For *VA perceptions*, we anticipate that performance and privacy risks may diminish positive emotions (Wei 2021). As Gao et al. (2018) show, users who treat Amazon's Alexa as a person (anthropomorphism) respond to it with more positive emotions than those who treat it as a technological device. *Shopping occasion perceptions* also might influence positive emotions. For example, good price value might reduce customers' doubts about fairness, so they might enjoy the VA more (Davis and Hodges 2012). When support from the retailer leads customers to perceive the VA as more easily accessible, it likely spurs positive emotions (Van der Heijden 2004). Social approval (social influence) positively correlates with emotions like pride (Fix et al. 2006). A perceived "socialness" of the shopping encounter (social presence) might enhance pleasure (Wang et al. 2007).

In contrast, *negative emotions* associated with VAs may inhibit technology use, in that emotions like anger and anxiety foster avoidance behavior (Li and Huang 2020; Mehrabian and Russell 1974). Among *customer characteristics*, competence, habit, and trust may counteract negative emotions. Competent customers are less likely to harbor negative feelings toward VAs (Clarkson et al. 2013), and habitual users gain feelings of safety and reassurance, mitigating negativity (Maslow 1970). Trust might act like a "stress buffer," combatting negative emotions from unreliable VAs (Johnson and Grayson 2005). Moreover, *VA perceptions* may relate to negative emotions. Specifically, overly humanlike VAs (anthropomorphism) might create unease due to the uncanny valley effect (Mori et al. 2012), and performance and privacy risks could evoke fear or anxiety (Loewenstein et al. 2001). Regarding *shopping occasion perceptions*, support from the retailer may reduce negative emotions by mitigating harm concerns (Ellway 2016). Unfavorable price value potentially instills negative emotions. If customers are not treated fairly—for example, in the prices charged—they might experience contempt or anger (Xia et al. 2004). Moreover, social influence can trigger discomfort, in the sense that peer pressure can make technology use unpleasant (Rains 2013). Finally, a pronounced perception of social presence during the shopping encounter may foster social bonding and mitigate negativity (Chircu et al. 2000).

1.4. Moderating effects

Examining the moderating effects of VA types represents an especially novel and worthwhile consideration (Venkatesh et al. 2016); most existing studies examine single VA types, without any comparisons, such that we thus far lack a strong, consistent theoretical foundation (Chen et al. 2021). The arguments for intertype comparisons are often weakly empirically supported, contradictory, or lacking (Table 2). Thus, to contrast findings across different VAs, we consider the moderating impacts of four VA types: intelligent versus less intelligent, commercial versus noncommercial, voice- versus text-based, and avatar- versus non-avatar-based.

Intelligent vs. *Less Intelligent VAs*. Advancements in AI enable modern VAs to provide vastly improved conversations and service provision through natural language processing, relative to simpler, script-based VAs (Huang and Rust 2021). Despite their greater problem-solving efficiency, intelligent VAs may adversely affect the relationships associated with some of our model variables if they evoke "algorithm aversion" (Castelo et al. 2019). This aversion, linked to anxiety about the threats of job losses, unethical actions, or privacy breaches due to AI, increases with VAs' greater autonomy (Li and Huang 2020). Although prior literature hints at such moderating effects for some of the relationships in our model, the effects on others are unclear (Table 2). Because intelligent VAs emulate natural language, they might facilitate emotion formation and enhance the effects of different antecedents on emotional responses (Huang and Rust 2021). Also, more intelligent—and thus more potentially frightening—VAs likely enhance the impact of performance and privacy risk considerations for determining cognitive and emotional responses (Li and Huang 2020). With their conversational capabilities, intelligent VAs tend to elicit social perceptions, which could accelerate the process of attributing human characteristics to them (Blut et al. 2021). Anthropomorphism also should become increasingly significant (Castelo et al. 2019; Mori et al. 2012). The effects of an intelligent VA on the links between shopping occasion perceptions (available support, price value, susceptibility to social influence, perceived social presence) and cognitive responses are unclear, though support or social influence might grow more important as means to mitigate AI anxiety (Fix et al. 2006; Li and Huang 2020). Finally, intelligent VAs may alter the relationship between cognitive responses and technology use, by raising customers' expectations of the VAs' usability and performance (Blut et al. 2022), as well as the relationships between emotional responses and technology use, by enhancing customers' sensitivity to emotions they evoke (Huang and Rust 2022).

Commercial vs. *Noncommercial VAs*. Existing VAs perform both commercial (e.g., e-commerce) and noncommercial (e.g., fashion advice) tasks. The financial implications of commercial tasks, such as purchasing through a chatbot, inherently evoke financial risks and make service quality more critical, due to the greater potential losses they imply, compared with noncommercial tasks (Blut et al. 2016). We find some evidence of moderating effects of this VA type for cognitive responses, though many effects remain unclear (Table 2). For commercial tasks, customer characteristics such as competence, habit, and trust might be especially crucial drivers of cognitive responses, because they help mitigate financial loss concerns (Gashami et al. 2014). Moreover, performance and privacy risks likely affect cognitive responses in commercial tasks, by making customers more risk-averse (Gashami et al. 2014). Anthropomorphism may be more important in commercial contexts too, in that customers tend to feel more comfortable and worry less when interacting with a humanlike entity (Blut et al. 2021). The effects of these antecedents on emotional responses are unclear though. Heightened risk for commercial tasks could lead to stronger initial emotional responses to different shopping occasion perceptions (Lazarus 1991), or customers might assess these situations more rationally, which would reduce the impact of emotional triggers (Hasan et al. 2020). Regarding technology use, task type could affect relationships with both emotional and cognitive responses. For example, perceived ease of use and usefulness might exert greater influences on technology use for commercial tasks due to customers' financial awareness, but emotional factors may have a less significant role, due to the generally rational nature of commercial settings (Hasan et al. 2020).

Voice- vs. *Text-Based VAs*. We can categorize VAs on the basis of their communication modality: voice-based (e.g., Siri, Alexa) or text-based (e.g., Replika, Facebook chatbots). Voice-based VAs rely on voice recognition and speech synthesis, whereas text-based VAs offer preset or AI-generated text responses. Despite weak evidence, prior literature indicates some moderating effects for emotional and cognitive responses (Table 2). Regarding customer characteristics, voice-based VAs require less cognitive effort, because speaking is more natural than writing (Kock 2004; Le Bigot et al. 2007). Thus, compe-

Table 2
Rationales for moderating effects.

Relationship		Intelligent VAs		Commercial tasks		Voice-based VAs		Avatar VAs
Cognitive responses								
Competence → Ease of use, usefulness	?	(unclear)	+	... competence gains importance because it mitigates financial loss concerns (Gashami et al. 2014)	–	... competence diminishes in importance because these VAs require less cognitive effort (Le Bigot et al. 2007)	+	... competence is more crucial because these VAs make interactions reciprocal and interactive (Holzwarth et al. 2006)
Habit → Ease of use, usefulness	?	(unclear)	+	... habit gains importance because it mitigates financial loss concerns (Gashami et al. 2014)	–	... habit diminishes in importance because these VAs require less cognitive effort (Le Bigot et al. 2007)	+	... habit is more crucial because these VAs make interactions reciprocal and interactive (Holzwarth et al. 2006)
Trust → Ease of use, usefulness	?	(unclear)	+	... trust gains importance because it mitigates financial loss concerns (Gashami et al. 2014)	–	... trust diminishes in importance because these VAs require less cognitive effort (Le Bigot et al. 2007)	+	... trust is more crucial because these VAs make interactions reciprocal and interactive (Holzwarth et al. 2006)
Anthropomorphism → Ease of use, usefulness	+	... anthropomorphism gains importance because these VAs accelerate attributions of human characteristics (Blut et al. 2021)	+	... anthropomorphism gains importance because it mitigates financial loss worries (Frank et al. 2023)	?	(unclear)	+	... anthropomorphism gains importance because these VAs are more noticeable through their animated and vivid appeal (Bartneck et al. 2009)
Performance/privacy risk → Ease of use, usefulness	+	... performance and privacy risks gain importance to mitigate AI anxiety tied to these VAs (Li and Huang 2020)	+	... performance and privacy risk gain importance because customers are more risk-averse (Gashami et al. 2014)	?	(unclear)	?	(unclear)
Support → Ease of use, usefulness	+	... support gains importance to mitigate AI anxiety related to these VAs (Li and Huang 2020)	?	(unclear)	–	... support is less important, because these VAs are more persuasive (Ischen et al. 2022)	–	... support diminishes in importance because these VAs enhance vividness and divert attention from shopping occasion (Noble et al. 2013)
Price value → Ease of use, usefulness	?	(unclear)	?	(unclear)	–	... price value is less important, because these VAs are more persuasive (Ischen et al. 2022)	–	... price value diminishes in importance because these VAs enhance vividness and divert attention from shopping occasion (Noble et al. 2013)
Social influence → Ease of use, usefulness	+	... social influence gains importance to mitigate AI anxiety related to these VAs (Li and Huang 2020)	?	(unclear)	–	... social influence is less important, because these VAs are more persuasive (Ischen et al. 2022)	–	... social influence diminishes in importance because these VAs enhance vividness and divert attention from shopping occasion (Noble et al. 2013)
Social presence → Ease of use, usefulness	?	(unclear)	?	(unclear)	–	... social presence is less important during shopping occasion, because these VAs are more persuasive (Ischen et al. 2022)	–	... social presence diminishes in importance because these VAs enhance vividness and divert attention from shopping context (Noble et al. 2013)
Emotional responses								
Competence → Position/negative emotions	+	...competence gains importance because these VAs facilitate emotion formation (Huang and Rust 2021)	?	(unclear)	+	... competence gains importance because these VAs mirror and amplify customer commands (Sailunaz et al. 2018)	?	(unclear)
Habit → Position/negative emotions	+	...habit gains importance because these VAs facilitate emotion formation (Huang and Rust 2021)	?	(unclear)	+	... habit gains importance because these VAs mirror and amplify customer commands (Sailunaz et al. 2018)	?	(unclear)

(continued on next page)

Table 2 (*continued*)

Relationship		Intelligent VAs		Commercial tasks		Voice-based VAs		Avatar VAs
Trust → Position/negative emotions	+	...trust gains importance because these VAs facilitate emotion formation (Huang and Rust 2021)	?	(unclear)	+	... trust gains importance because these VAs mirror and amplify customer commands (Sailunaz et al. 2018)	?	(unclear)
Anthropomorphism → Position/negative emotions	+	... anthropomorphism gains importance because these VAs accelerate the attribution of human characteristics (Blut et al. 2021)	?	(unclear)	±	...anthropomorphism is more effective in inducing positive emotions and reducing negative ones because these VAs are better in detecting and reflecting human emotions (Sailunaz et al. 2018)	+	... anthropomorphism gains importance because these VAs are more noticeable through their animated and vivid appeal (Bartneck et al. 2009)
Performance/privacy risk → Position/negative emotions	+	... performance and privacy risks gain importance because these VAs are more frightening (Li and Huang 2020)	?	(unclear)	–	... performance and privacy risks diminish in importance given advanced capabilities of managing doubt and fear (Latif et al. 2020)	?	(unclear)
Support → Position/negative emotions	+	...support gains importance because these VAs facilitate emotion formation (Huang and Rust 2021)	?	(unclear)	+	... support gains importance because these VAs are better in emotional transmission (Sailunaz et al. 2018)	?	(unclear)
Price value → Position/negative emotions	+	...price value gains importance because these VAs facilitate emotion formation (Huang and Rust 2021)	?	(unclear)	+	... price value gains importance because these VAs are better in emotional transmission (Sailunaz et al. 2018)	?	(unclear)
Social influence → Position/negative emotions	+	...social influence gains importance because these VAs facilitate emotion formation (Huang and Rust 2021)	?	(unclear)	+	... social influence gains importance because these VAs are better in emotional transmission (Sailunaz et al. 2018)	?	(unclear)
Social presence → Position/negative emotions	+	...social presence gains importance as these VAs facilitate emotion formation based on perceptions of social presence during the shopping occasion (Huang and Rust 2021)	?	(unclear)	+	... social presence gains importance during shopping occasion as these VAs are better in emotional transmission (Sailunaz et al. 2018)	?	(unclear)
Technology use								
Ease of use, usefulness → Behavioral intention, use	+	... ease of use and usefulness gain importance because these VAs raise customer expectations (Blut et al. 2022)	+	... ease of use and usefulness gain importance due to customers' greater financial awareness (Hasan et al. 2020)	–	... ease of use and usefulness diminish in relevance because these VAs reduce customers' cognitive load (Rzepka et al. 2022)	+	... ease of use and usefulness gain importance because these VAs are more noticeable and engaging (Bartneck et al. 2009; Chang and Lee 2010)
Position/negative emotions → Behavioral intention, use	+	... positive and negative emotions gain importance because these VAs enhance customers' sensitivity to emotions (Huang and Rust 2022)	–	... positive and negative emotions diminish in importance due to the rational nature of these settings (Shimp and Bearden 1982)	+	... positive and negative emotions gain importance because these VAs are more skilled in detecting emotions (Latif et al. 2020)	+	... positive and negative emotions gain importance because these VAs are more noticeable and engaging (Bartneck et al. 2009; Chang and Lee 2010)

Notes: Prior literature hints at positive (+) or negative (–) moderating effects, or provides contradictory or no (?) indication.

tence, habit, and trust may be less relevant for driving cognitive responses. Similarly, shopping occasion perceptions should be less important, because voice-based VAs are more persuasive than text-based VAs (Ischen et al. 2022). We find no evidence regarding the impact of communication modality on the relationship between VA perceptions and cognitive responses though. Regarding emotional responses, voice-based VAs process both verbal and vocal cues, so they are better suited for emotional information transmission than text-based VAs. Joyful commands from competent, habitual, and trusting customers may be better mirrored and amplified by voice-based VAs, which are adept at detecting human emotions through changes in pitch, volume, speed, and tone (Sailunaz et al. 2018); these customer characteristics then may exert stronger effects on emotional responses. Also, the impact of anthropomorphism on positive emotions could be more pronounced when communicated by voice, which offers more cues to convey the VA's human-like nature. If advanced, voice-based VAs can detect negative emotional responses from customers promptly and counteract them, it might weaken the impact of anthropomorphism on negative emotions. For similar reasons, the influence of performance and privacy risks on emotional responses might be lessened by voice-based VAs, reflecting their strong capabilities for managing doubt and fear (Latif et al. 2020). The emotional impact of shopping occasion perceptions (available support, price value, susceptibility to social influence, perceived social presence) also could be stronger in voice-based interactions, due to the better emotional transmission they provide (Sailunaz et al. 2018). Whereas voice-based VAs might enhance the link between emotional responses and technology use, through the skillful detection and expression of emotions (Latif et al. 2020), such communication could reduce customers' cognitive load, making usability (ease of use) and performance (usefulness) less relevant drivers of technology use (Rzepka et al. 2022).

Avatar- vs. Non-Avatar-Based VAs. Defined as "generic graphic representations personified by means of computer technology" (Holzwarth et al. 2006, p. 20), avatars represent some VAs, ranging from simple, cartoon-like images to realistic figures (e.g., Replika; Miao et al. 2022). Appearing like robots, animals, or other entities, they enhance lifelike and animacy perceptions through visual appeal, leading customers to view VAs as independently interactive entities (Balakrishnan and Dwivedi 2024).[3] For avatar-based VAs, customer characteristics such as competence, trust, and habit might be crucial in driving cognitive responses, because the engaging avatars make the computer interactions more reciprocal and require more interaction skills from customers (Holzwarth et al. 2006). Whereas their impact on the relationships between risk perceptions and cognitive responses is unclear, avatar-based VAs likely amplify the effects of anthropomorphism, because customers find them convincing during interactions (Blut et al. 2021). They also might boost the impact of anthropomorphism on positive emotions or exacerbate the uncanny valley effect, leading to stronger negative emotions (Mori et al. 2012). Because avatars enhance vividness (Noble et al. 2013), they divert customers' attention from contextual factors, like shopping occasion perceptions (available support, price value, susceptibility to social influence, perceived social presence), so they should weaken the relationships of such perceptions with cognitive responses. The moderating influence of avatar-based VAs on the links of customer characteristics and shopping occasion perceptions with emotional responses may vary. Lifelike avatars can amplify the influence of emotional triggers on emotional responses (Bartneck et al. 2009), but they also might distract customers, due to their vividness (Noble et al. 2013), potentially weakening the effects of customer and shopping occasion factors. Regarding technology use, avatars make VAs more noticeable and engaging (Chang and Lee 2010), so customers might be more likely to notice their usability (ease of use) and performance (usefulness). For similar reasons, emotional responses may be more substantial drivers of technology use (Bartneck et al. 2009).

1.5. Context and method moderators

To explore whether the effect sizes differ across other potential moderators, we test the influences of other context and method differences. For example, differences might arise between retailing and service contexts, in that services feature greater intangibility, which may influence VA perceptions. We also test for study sampling differences, that is, whether the VAs can be used in single- or multiple-industry settings. Respondents in single industries may be more alike, so the error variance may be lower in these samples, leading to stronger effect sizes (Hunter and Schmidt 2004). To address potential publication bias, we consider publication status. The publication of nonsignificant effects is less likely in journals than in conference proceedings and dissertations (Hunter and Schmidt 2004). Experimental studies may display stronger effect sizes than surveys, because they control for the influence of extraneous variables (Blut et al. 2021). Finally, we assess journal quality differences. Studies published in higher-quality journals undergo rigorous mechanisms, which should reduce the presence of factors that tend to inflate effect sizes (Hunter and Schmidt 2004).

2. Method

We searched several electronic databases for relevant studies (i.e., ABI/INFORM, Proquest, EBSCO Business Source Premier, and Google Scholar); we searched for keywords in 39 retailing, services, and marketing journals and 94 information systems journals, using the Academic Journal Guide 2018. We also reviewed the reference lists of all identified studies. The search included unpublished data sets and grey literature, conference proceedings, and dissertation databases. After our initial search, we updated the database on June 5, 2023. In addition, we extracted 839 email addresses from authors of the studies identified in our literature search, approached them, and asked them to share the results of any unpublished work. Excluding conceptual papers and qualitative studies left 195 usable studies for the meta-analysis (Web Appendixes C–D). We used correlation coefficients as effect sizes, which are scale-free and frequently appear in the collected studies. If the correlation coefficients were not reported, we converted other statistical information, such as regression coefficients (Peterson and Brown 2005). When an independent sample reported more than one effect size for the same relationship, we

[3] These examples illustrate the difference between anthropomorphism and avatars: Anthropomorphism refers to humanization of non-human entities, but avatars are virtual embodiments that can take diverse forms, beyond human-like (Nowak and Fox 2018).

averaged effect sizes to avoid giving single samples too much weight in the subsequent analyses. After averaging the effect sizes, the data set included 2766 correlations reported for 244 independent samples by 195 studies. Coders classified the effect sizes according to construct definitions in Table 1 and coded the moderators. The agreement rate among the coders was 98%.

We used the meta-analytic approach recommended by Hunter and Schmidt (2004), which is a random effect approach to integrating effect sizes. Thus, the effect sizes were corrected for different artifacts (measurement error, sampling error). In addition to 95% confidence intervals, we calculated credibility intervals. We prepared χ^2 tests of homogeneity and I^2 statistics to assess heterogeneity in the effect sizes (Grewal et al. 2018). Rosenthal's (1979) fail-safe N (FSN) and funnel plots were prepared. Finally, we employed moderator analyses and structural equation modeling (SEM).[4] Web Appendix E details the approaches to the effect size integration and multivariate analyses.

3. Results

3.1. Descriptive results

Table 3 contains the results of the effect size integration, which provide initial insights into the direct and indirect effects of different customer characteristics, VA perceptions, and shopping occasion perceptions on technology use. We discuss these effect size integration results briefly, because we also test the model with SEM, which represents a more sophisticated method.

With few exceptions, the effect sizes are significant (Table 3). First, we find indications of indirect effects through *cognitive responses*, indicating that most antecedents significantly influence cognitive responses. Specifically, we observe the strongest effects on *ease of use* for support (sample-weighted, reliability-adjusted average correlation [rwc] = .67, $p < .05$) and price value (rwc = .59, $p < .05$), followed by competence (rwc = .46, $p < .05$) and trust (rwc = .45, $p < .05$); only performance risk is nonsignificant. Regarding *usefulness*, the strongest effects arise for habit (rwc = .70, $p < .05$), price value (rwc = .65, $p < .05$), and ease of use (rwc = .62, $p < .05$); privacy risk is nonsignificant. Second, we find some indications of indirect effects through *emotional responses*, which appear significantly related to most antecedents. For *positive emotions*, the strongest effect sizes emerge for price value (rwc = .67, $p < .05$), followed by social presence (rwc = .58, $p < .05$) and habit (rwc = .57, $p < .05$). Privacy risk is nonsignificant. Regarding *negative emotions*, we find the strongest effect sizes for performance risk (rwc = .61, $p < .05$), support (rwc = −.52, $p < .05$), and price value (rwc = −.49, $p < .05$). All other effect were significant too. Third, we identify significant direct effects of most customer characteristics, VA perceptions, and shopping occasion perceptions on *behavioral intentions*, except for performance risk. Also, most responses show significant effects on behavioral intentions, including ease of use (rwc = .50, $p < .05$), usefulness (rwc = .63, $p < .05$), and positive emotions (rwc = .59, $p < .05$). Negative emotions are the only responses that are nonsignificant. All customer characteristics, VA perceptions, and shopping occasion perceptions relate to *use*. Also, all responses are significantly related to use, including ease of use (rwc = .43, $p < .05$), usefulness (rwc = .48, $p < .05$), positive emotions (rwc = .47, $p < .05$), and negative emotions (rwc = −.32, $p < .05$), as well as behavioral intentions (rwc = .52, $p < .05$).

The significant Q-tests, I^2 statistics ($I^2 > 75\%$), and wide credibility intervals suggest substantial variance in effect sizes (Table 3; Web Appendix G). The power tests indicate that most statistical analyses have sufficient power (>.8; (Cohen 1992); Web Appendix G). We do not find any indication of publication bias. The FSNs exceed the tolerance levels suggested by Rosenthal (1979) in 64 of 65 cases (98%), and the funnel plots are symmetric (Web Appendix H). Also, the results are robust to effect size and sample size outliers (Web Appendix I).

3.2. SEM results

In using SEM to assess our conceptual model, we take covariation among variables into account, such that we expect the results of the effect size integration to differ from these outcomes in terms of observed significance (Grewal et al. 2018). We used the correlation matrix in Web Appendix J as the input for our calculations and $N = 2949$ (harmonic mean) as the sample size. Including all parameters in the model at the same time would saturate the model, and we could not report model fit. We therefore gradually added the different antecedents. If individual antecedents appeared nonsignificant, we removed them from the model, to ensure enough degrees of freedom to report model fit. The results, in Table 4, indicate the good fit of the model (comparative fit index [CFI] = .93; goodness of fit index [GFI] = .93; root mean square residual [RMR] = .04; standardized RMR [SRMR] = .04).

Cognitive Responses. Most antecedents affect cognitive responses. The comparison of the *ease-of-use* antecedents reveals support ($\gamma = .48$, $p < .01$) as the strongest predictor, followed by price value ($\gamma = .27$, $p < .01$); the effects of social influence ($\gamma = .08$, $p < .01$) and anthropomorphism ($\gamma = .04$, $p < .05$) are relatively weaker. Competence, trust, and performance risk are nonsignificant. Among the antecedents, price value ($\gamma = .23$, $p < .01$) is the strongest predictor of *usefulness*, followed by social influence ($\gamma = .20$, $p < .01$); the effects of trust ($\gamma = .12$, $p < .01$), anthropomorphism ($\gamma = .10$, $p < .01$), and

[4] The results of the subgroup and regression analyses are observational; they cannot prove causality. Thus, experimental studies are required to validate the causal nature of the moderator findings (Grewal et al. 2018).

Table 3
Descriptive results: factors influencing cognitive and emotional responses and technology use.

Relationship	k	N	Assumption	rwc	Q	FSN	Relationship	k	N	Assumption	rwc	Q	FSN
Cognitive responses							**Emotional responses**						
Competence → Ease of use	22	4078	+	.46*	240*	6036	Competence → Positive emotions	17	2604	+	.34*	121*	1579
Habit → Ease of use	13	2320	+	.41*	15	1316	Habit → Positive emotions	14	2735	+	.57*	47*	3457
Trust → Ease of use	42	11,934	+	.45*	681*	29,557	Trust → Positive emotions	43	12,470	+	.51*	671*	38,713
Anthropomorphism → Ease of use	34	9111	+	.37*	311*	11,185	Anthropomorphism → Positive emotions	28	6133	+	.51*	224*	13,120
Performance risk → Ease of use	16	3590	–	–.18	391*	–	Performance risk → Positive emotions	14	2301	–	–.29*	117*	742
Privacy risk → Ease of use	33	9881	–	–.15*	622*	2689	Privacy risk → Positive emotions	30	9102	–	–.05	920*	–
Support → Ease of use	22	4678	+	.67*	163*	10,951	Support → Positive emotions	15	3362	+	.53*	47*	3532
Price value → Ease of use	17	3646	+	.59*	51*	6090	Price value → Positive emotions	20	4386	+	.67*	72*	10,749
Social influence → Ease of use	42	12,215	+	.39*	782*	18,681	Social influence → Positive emotions	22	5110	+	.48*	96*	7378
Social presence → Ease of use	23	6152	+	.29*	207*	3710	Social presence → Positive emotions	37	11,404	+	.58*	326*	40,118
Competence → Usefulness	24	5511	+	.27*	205*	3248	Competence → Negative emotions	16	2693	–	–.28*	183*	1225
Habit → Usefulness	13	2320	+	.70*	54*	4048	Habit → Negative emotions	10	1223	–	–.46*	8	711
Trust → Usefulness	56	18,914	+	.61*	902*	104,270	Trust → Negative emotions	14	2770	–	–.35*	281*	1598
Anthropomorphism → Usefulness	40	11,607	+	.47*	551*	27,044	Anthropomorphism → Negative emotions	16	464,143	+	.05*	280*	35
Performance risk → Usefulness	18	3842	–	–.20*	436*	1126	Performance risk → Negative emotions	13	2473	+	.61*	57*	2775
Privacy risk → Usefulness	36	11,684	–	–.04	1275*	–	Privacy risk → Negative emotions	17	3775	+	.44*	177*	3128
Support → Usefulness	22	5386	+	.56*	79*	7884	Support → Negative emotions	11	1238	–	–.52*	12	904
Price value → Usefulness	20	4808	+	.65*	100*	12,100	Price value → Negative emotions	11	1623	–	–.49*	160*	1632
Social influence → Usefulness	42	12,215	+	.56*	314*	42,014	Social influence → Negative emotions	12	1425	+	–.32*	50*	549
Social presence → Usefulness	32	10,056	+	.61*	365*	29,171	Social presence → Negative emotions	13	1740	–	–.31*	73*	556
Ease of use → Usefulness	87	25,737	+	.62*	1308*	216,309	–						
Behavioral intention							**Use**						
Competence → Behavioral intention	26	6058		.34*	185*	5377	Competence → Use	12	2097		.28*	52*	665
Habit → Behavioral intention	14	2603		.65*	77*	4206	Habit → Use	12	1844		.65*	69*	2880
Trust → Behavioral intention	62	18,300		.53*	1575*	90,361	Trust → Use	19	5110		.32*	426*	3673
Anthropomorphism → Behavioral intention	45	11,339		.50*	387*	31,960	Anthropomorphism → Use	15	4121		.36*	124*	2221
Performance risk → Behavioral intention	21	5123		–.08	695*	–	Performance risk → Use	11	1353		–.18*	60*	137
Privacy risk → Behavioral intention	49	15,514		–.14*	1156*	4621	Privacy risk → Use	16	3740		–.20*	101*	675
Support → Behavioral intention	26	6640		.47*	253*	9449	Support → Use	13	2096		.43*	8	1273
Price value → Behavioral intention	24	6166		.57*	274*	14,391	Price value → Use	13	2065		.41*	78*	1576
Social influence → Behavioral intention	52	12,768		.51*	394*	39,657	Social influence → Use	18	3803		.41*	152*	3550
Social presence → Behavioral intention	40	11,908		.53*	297*	34,542	Social presence → Use	17	4716		.43*	169*	3201
Ease of use → Behavioral intention	90	26,139	+	.50*	2456*	142,516	Ease of use → Use	22	6617	+	.43*	278*	6050
Usefulness → Behavioral intention	114	36,802	+	.63*	1307*	453,543	Usefulness → Use	27	8583	+	.48*	306*	15,728
Positive emotions → Behavioral intention	73	25,103	+	.59*	989*	180,162	Positive emotions → Use	20	5245	+	.47*	177*	6524
Negative emotions → Behavioral intention	20	4477	–	–.11	822*	–	Negative emotions → Use	11	1623	–	–.32*	94*	729
—							Behavioral intention → Use	22	7059	+	.52*	258*	12,641

Notes: k = number of effect sizes, N = cumulative sample size, rwc = sample-weighted, reliability-adjusted average correlation, Q = Q statistic. FSN = Fail-safe N. * $p < .05$. The number of effect sizes (k) equals the number of independent samples; when an independent sample reported more than one effect size for the same relationship, we averaged the effect sizes to avoid giving single samples too much weight in the analysis. We estimated the FSN only for those effect sizes (rwc) that were significant at the .05-level.

Table 4
SEM results.

Relationship	Assumption	B	p-value	R^2
Cognitive responses				
Competence → Ease of use	+	–		52%
Trust → Ease of use	+	–		
Anthropomorphism → Ease of use	+	.04*	.02	
Performance risks → Ease of use	–	–		
Support → Ease of use	+	.48**	<.01	
Price value → Ease of use	+	.27**	<.01	
Social influence → Ease of use	+	.08**	<.01	
Competence → Usefulness	+	–		59%
Trust → Usefulness	+	.12**	<.01	
Anthropomorphism → Usefulness	+	.10**	<.01	
Performance risks → Usefulness	–	–		
Support → Usefulness	+	.08**	<.01	
Price value → Usefulness	+	.23**	<.01	
Social influence → Usefulness	+	.20**	<.01	
Ease of use → Usefulness	+	.26**	<.01	
Emotional responses				
Competence → Positive emotions	+	–		54%
Trust → Positive emotions	+	–		
Anthropomorphism → Positive emotions	+	.23**	<.01	
Performance risk → Positive emotions	–	–.09**	<.01	
Support → Positive emotions	+	.12**	<.01	
Price value → Positive emotions	+	.43**	<.01	
Social influence → Positive emotions	+	.10**	<.01	
Competence → Negative emotions	–	–		60%
Trust → Negative emotions	–	–		
Anthropomorphism → Negative emotions	+	.42**	<.01	
Performance risk → Negative emotions	+	.37**	<.01	
Support → Negative emotions	–	–.27**	<.01	
Price value → Negative emotions	–	–.31**	<.01	
Social influence → Negative emotions	+	–.19**	<.01	
Technology use				
Competence → Behavioral intention		.08**	<.01	52%
Trust → Behavioral intention		.07**	<.01	
Anthropomorphism → Behavioral intention		.15**	<.01	
Performance risks → Behavioral intention		–		
Support → Behavioral intention		–		
Price value → Behavioral intention		.06**	<.01	
Social influence → Behavioral intention		.12**	<.01	
Ease of use → Behavioral intention	+	.05**	<.01	
Usefulness → Behavioral intention	+	.26**	<.01	
Positive emotions → Behavioral intention	+	.17**	<.01	
Negative emotions → Behavioral intention	–	–		
Competence → Use		–		40%
Trust → Use		–		
Anthropomorphism → Use		.13**	<.01	
Performance risks → Use		–		
Support → Use		–		
Price value → Use		–		
Social influence → Use		–		
Ease of use → Use	+	.08**	<.01	
Usefulness → Use	+	.13**	<.01	
Positive emotions → Use	+	–		
Negative emotions → Use	–	–.25**	<.01	
Behavioral intention → Use	+	.31**	<.01	

** $p < .01$; * $p < .05$. Notes: The estimates in the table are standardized. A dash (–) indicates a nonsignificant path coefficient. Including all parameters in the model at the same time would saturate the model, and we could not report model fit. We therefore gradually added the different antecedents. If individual antecedents appeared nonsignificant, we removed them from the model, to ensure enough degrees of freedom to report model fit. Model fit: CFI = .93; GFI = .93; RMR = .04; SRMR = .04.

support (γ = .08, p < .01) are weaker; and competence and performance risk are nonsignificant. Ease of use (γ = .26, p < .01) also affects usefulness.

Emotional Responses. Most of the antecedents affect emotional responses. With a comparison of antecedents, we determine that price value (γ = .43, p < .01) is the strongest predictor of *positive emotions*, followed by anthropomorphism (γ = .23, p < .01). The effects of support (γ = .12, p < .01), social influence (γ = .10, p < .01), and performance risk (γ = −.09, p < .01) are weaker, and competence and trust are nonsignificant. For *negative emotions*, anthropomorphism (γ = .42, p < .01) is the strongest predictor, followed by performance risk (γ = .37, p < .01), price value (γ = −.31, p < .01), and support (γ = −.27, p < .01). The effect of social influence (γ = −.19, p < .01) is weaker, and again, competence and trust are nonsignificant.

Technology Use. Several antecedents have direct effects on *behavioral intentions*. Among the antecedents, anthropomorphism (β = .15, p < .01) and social influence (β = .12, p < .01) represent the strongest predictors, followed by competence (β = .08, p < .01), trust (β = .07, p < .01), and price value (β = .06, p < .01). Performance risk and support have no influence on behavioral intentions. Also, ease of use (β = .05, p < .01), usefulness (β = .26, p < .01), and positive emotions (β = .17, p < .01) affect behavioral intentions. Negative emotions are nonsignificant. Moreover, anthropomorphism (β = .13, p < .01) is the only antecedent with a direct impact on *use*. Among all mediators, negative emotions (β = −.25, p < .01) exert the strongest effects, though usefulness (β = .13, p < .01) and ease of use (β = .08, p < .01) also affect use directly. Positive emotions show no direct impact. Finally, behavioral intentions influence use (β = .31, p < .01).

Indirect and Total Effects. We report the indirect and total effects of the SEM in Web Appendix K. These analyses provide insights into the importance of specific mediating relationships, as well as the overall importance of the different antecedents for driving technology use. First, most relationships between antecedents and use are fully mediated; only a few are partially or not mediated. Anthropomorphism, support, price value, and social influence operate through all mediators, though their strongest indirect effects move through negative emotions. Trust exerts indirect effects through cognitive responses (usefulness) exclusively; performance risk exerts indirect effects through emotional responses, especially negative emotions. Competence is the only antecedent that does not exert indirect effects on use through cognitive or emotional responses. Second, the total effects of the SEM indicate the overall importance of different antecedents for driving technology use. We identify price value as the strongest driver of use, followed by support, social influence, and anthropomorphism. Performance risk, competence, and trust matter too, but to a lesser extent.

3.3. Moderator results

With meta-regression, we explore which VA types influence (1) the impacts of different antecedents on cognitive and emotional responses and (2) the impacts of these responses on technology use. The results are in Table 5 and Web Appendix L. We regress the reliability-corrected effect sizes on four substantive moderators and five context and method moderators. By applying regression analysis to test the moderating effects, we can account for the influence of all potential moderators at the same time (Grewal et al. 2018). For this analysis, we reverse the effect sizes of the antecedents with a negative main effect (Table 3), to ease interpretation of the moderator analysis; a positive (negative) regression coefficient suggests an enhancing (weakening) moderating effect. Grewal et al. (2018) also stress the importance of testing for multicollinearity in meta-regressions; the reported variance inflation factors, which range between 1.02 and 6.72, indicate it is not a problem. The results of the regression analysis using subgroup analyses (Web Appendix M) are similar.

Intelligent vs. *Less Intelligent VAs.* This moderator reveals several significant effects. Regarding *ease of use*, intelligent VAs enhance the positive effects of support (b = .84, p < .05) and social presence (b = .56, p < .05). Regarding *usefulness*, intelligent VAs enhance the negative effects of performance risk (b = .43, p < .05) and privacy risk (b = .57, p < .05) and the positive effect of support (b = .97, p < .05). They weaken the positive effect of social presence (b = −.73, p < .05) on usefulness. Regarding *positive emotions*, intelligent VAs enhance the positive effect of habit (b = .35, p < .05). Furthermore, this moderator enhances the negative effects of competence (b = .67, p < .05) and support (b = .48, p < .05) on *negative emotions*, as well as the positive effect of anthropomorphism (b = .35, p < .05). Moreover, intelligent VAs weaken the negative effect of social presence (b = −.55, p < .05) on negative emotions. The intelligence of the VA also moderates some relationships between responses and technology use: It weakens the positive effect of positive emotions on *behavioral intention* (b = −.35, p < .05) but enhances the negative effect of negative emotions on *use* (b = .59, p < .05).

Commercial vs. *Noncommercial VAs.* We find fewer significant differences when we compare VAs that perform commercial versus noncommercial tasks. First, commercial tasks enhance the negative effect of privacy risk (b = .29, p < .05) on *ease of use*. No significant differences arise for *usefulness*. Instead, commercial tasks weaken the positive effects of habit (b = −.33, p < .05) and support (b = −.39, p < .05) on *positive emotions* but enhance the positive effect of social influence (b = .38, p < .05). No significant differences arise for *negative emotions*. Second, commercial tasks weaken the positive effect of positive emotions (b = −.30, p < .05) on *behavioral intentions*. We observe no significant differences for *use*.

Voice- vs. *Text-Based VAs.* Several significant differences arise from the comparison of voice-based and text-based VAs. First, regarding *ease of use*, voice-based VAs weaken the positive effects of anthropomorphism (b = −.63, p < .05), support (b = −.70, p < .05), and social presence (b = −.92, p < .05) on this response, but they strengthen the negative effect of performance risk (b = .93, p < .05). We also observe that voice-based VAs weaken the positive effects of support (b = −.60, p < .05) and price value (b = −.57, p < .05) on *usefulness*. In addition, they strengthen the positive effects of competence (b = .49, p < .05) and social influence (b = .90, p < .05) on *positive emotions* but weaken the positive effects of price value

Table 5
Results of moderator tests using meta-regression.

IV	DV	k	Assum.[c]	1 = Intelligent 0 = Less intelligent	Assum.	1 = Commercial tasks 0 = Noncommercial	Assum.	1 = Voice-based 0 = Text-based	Assum.	1 = Avatar-based 0 = Non-avatar-based	Context and method moderators[b]	R^2	VIF
Cognitive responses													
Competence	Ease of use	22	?	.35	+	.04	–	−.11	+	.30*	Included	47%	2.76
Habit	Ease of use	13	?	.24	+	−.04	–	—	+	.22	Included	45%	1.22
Trust	Ease of use	42	?	.03	+	.02	–	−.05	+	.09	Included	9%	2.96
Anthropomorphism	Ease of use	34	+	.28	+	.08	?	−.63*	+	−.28	Included	56%	3.77
Performance risk[a]	Ease of use	16	+	−.56	+	.09	?	.93*	?	—	Included	35%	5.80
Privacy risk[a]	Ease of use	33	+	−.12	+	.29*	?	.23	?	—	Included	22%	3.20
Support	Ease of use	22	+	.84*	?	.15	–	−.70*	–	.21	Included	59%	4.44
Price value	Ease of use	17	?	−.34	?	−.13	–	−.20	–	−.63*	Included	69%	6.35
Social influence	Ease of use	42	+	−.01	?	−.19	–	−.03	–	−.10	Included	30%	2.70
Social presence	Ease of use	23	?	.56*	?	−.16	–	−.92*	–	.55*	Included	61%	5.63
Competence	Usefulness	24	?	−.18	+	.03	–	.45	+	.48*	Included	34%	5.06
Habit	Usefulness	13	?	.03	+	−.28	–	—	+	−.17	Included	73%	1.22
Trust	Usefulness	56	?	.02	+	.14	–	−.16	+	.00	Included	10%	2.08
Anthropomorphism	Usefulness	40	+	−.16	+	.13	?	.09	+	.28	Included	34%	3.67
Performance risk[a]	Usefulness	18	+	.43*	+	.04	?	—	?	.27	Included	43%	2.31
Privacy risk[a]	Usefulness	36	+	.57*	+	−.16	?	−.40	?	.03	Included	25%	3.14
Support	Usefulness	22	+	.97*	?	−.08	–	−.60*	–	−.43	Included	30%	4.94
Price value	Usefulness	20	?	.18	?	.07	–	−.57*	–	−.21	Included	79%	6.02
Social influence	Usefulness	42	+	−.14	?	−.19	–	.03	–	−.02	Included	10%	2.70
Social presence	Usefulness	32	?	−.73*	?	−.07	–	−.03	–	.13	Included	60%	5.22
Emotional responses													
Competence	Positive emotions	17	+	−.01	?	−.10	+	.49*	?	.46*	Included	74%	3.56
Habit	Positive emotions	14	+	.35*	?	−.33*	+	—	?	.16	Included	57%	1.19
Trust	Positive emotions	43	+	−.23	?	−.26	+	−.17	?	.18	Included	26%	2.29
Anthropomorphism	Positive emotions	28	+	−.27	?	−.02	+	.34	+	.18	Included	27%	3.25
Performance risk[a]	Positive emotions	14	+	.23	?	.09	–	—	?	−.91*	Included	74%	1.29
Privacy risk[a]	Positive emotions	30	+	.29	?	−.02	–	.00	–	—	Included	18%	3.66
Support	Positive emotions	15	+	.24	?	−.39*	+	—	?	−.19	Included	55%	6.20
Price value	Positive emotions	20	+	.25	?	−.10	+	−.80*	?	−.35*	Included	59%	3.72

(*continued on next page*)

Table 5 (*continued*)

IV	DV	k	Assum.[c]	1 = Intelligent 0 = Less intelligent	Assum.	1 = Commercial tasks 0 = Noncommercial	Assum.	1 = Voice-based 0 = Text-based	Assum.	1 = Avatar-based 0 = Non-avatar-based	Context and method moderators[b]	R^2	VIF
Social influence	Positive emotions	22	+	−.69	?	.38*	+	.90*	?	−.13	Included	26%	6.72
Social presence	Positive emotions	37	+	−.27	?	−.04	+	−.16	?	.20	Included	36%	2.64
Competence[a]	Negative emotions	16	+	.67*	?	.09	+	−.30	?	.11	Included	73%	4.04
Habit[a]	Negative emotions	10	+	.32	?	−.03	+	—	?	—	Included	11%	1.03
Trust[a]	Negative emotions	14	+	−.05	?	−.11	+	.12	?	.24	Included	16%	4.49
Anthropomorphism	Negative emotions	16	+	.35*	?	−.16	–	.18	+	.74*	Included	77%	4.82
Performance risk	Negative emotions	13	+	.16	?	−.24	–	—	?	—	Included	26%	2.50
Privacy risk	Negative emotions	17	+	.28	?	−.21	–	−.18	–	.26	Included	17%	3.15
Support[a]	Negative emotions	11	+	.48*	?	.26	+	—	?	—	Included	30%	1.05
Price value[a]	Negative emotions	11	+	−.26	?	.23	+	—	?	—	Included	20%	1.02
Social influence[a]	Negative emotions	12	+	−.19	?	.36	+	—	?	—	Included	51%	6.18
Social presence[a]	Negative emotions	13	+	−.55*	?	−.06	+	.05	?	−.88*	Included	93%	4.71
Technology use													
Ease of use	Behavioral intention	90	+	.19	+	−.14	–	−.20	+	.09	Included	7%	2.17
Usefulness	Behavioral intention	114	+	−.15	+	−.02	–	−.00	+	.05	Included	12%	1.86
Positive emotions	Behavioral intention	73	+	−.35*	–	−.30*	+	.08	+	.07	Included	25%	2.12
Negative emotion[a]	Behavioral intention	20	+	−.20	–	.04	+	.30	+	.47*	Included	73%	3.41
Ease of use	Use	22	+	.25	+	.11	–	−.04	+	.00	Included	10%	2.00
Usefulness	Use	27	+	.17	+	.02	–	.50*	+	−.32	Included	42%	6.16
Positive emotions	Use	20	+	.22	–	−.25	+	−.01	+	−.02	Included	17%	2.46
Negative emotion[a]	Use	11	+	.59*	–	.29	+	—	+	—	Included	46%	1.02

* $p < .05$. k = number of effect sizes. VIF= Maximum variance inflation factor. The displayed estimates are regression weights; for example, the positive regression coefficient of intelligence (.84) for support-ease of use relationship suggests that this positive association is stronger for VAs of high intelligence than low intelligence; a negative regression coefficient would suggest a weakening effect. [a]We reversed the effect sizes for this analysis to ease interpretability; a positive (negative) coefficient suggests an enhancing (weakening) moderating effect. A dash indicates that a moderator could not be tested. [b]Web Appendix L provides detailed results, with context and method moderators. [c] Prior literature hints at positive (+) or negative (–) moderating effects, or provides contradictory or no (?) indication.

($b = -.80$, $p < .05$). No significant differences emerge for *negative emotions*. Second, we find few significant differences for technology use. The positive effect of usefulness on *use* is stronger ($b = .50$, $p < .05$) with voice-based VAs, but we note no significant differences for *behavioral intentions*.

Avatar- vs. *Non-Avatar-Based VAs.* Several differences are evident for VAs that rely on avatars. First, avatar-based VAs enhance the positive effects of competence ($b = .30$, $p < .05$) and social presence ($b = .55$, $p < .05$) on *ease of use*, but they weaken the positive effect of price value ($b = -.63$, $p < .05$). For *usefulness*, we find avatar-based VAs enhance the positive effect of competence ($b = .48$, $p < .05$). Regarding *positive emotions*, avatar-based VAs enhance the positive effect of competence ($b = .46$, $p < .05$) but weaken the negative effect of performance risk ($b = -.91$, $p < .05$) and the positive effect of price value ($b = -.35$, $p < .05$). This moderator enhances the positive effect of anthropomorphism ($b = .74$, $p < .05$) on *negative emotions* and weakens the negative effect of social presence ($b = -.88$, $p < .05$). Second, in relation to technology use, avatar-based VAs enhance the negative effect of negative emotions ($b = .47$, $p < .05$) on *behavioral intentions* but indicate no significant differences for *use*.

Context and Method Moderators. Some context and method moderators indicate significant effects (Web Appendix L). Yet we do not find dramatic differences between service and retailing contexts: The positive effect of social presence on usefulness is stronger for service than retailing, and the negative effect of competence on negative emotions is weaker. Although they suggest some interesting context and method differences, the results of testing the various VA types remain the same when we account for industry differences, number of examined industries, publication status, study design, and quality of the publication outlet.

4. Discussion

To help retailers introduce VAs effectively and convert customers into repeat users, we seek to establish clear guidance, while also supporting theory building in this research domain. With our meta-analysis, we synthesize extant empirical research into factors that influence VA use, assess the mediating roles of customers' cognitive and emotional responses to VAs, and compare the performance of major VA types. In addition to summarizing the key contributions of our meta-analysis in Table 6, we detail their implications for academics and retailers next.

4.1. Which factors lead customers to use VAs?

Our meta-analysis provides a comprehensive view of the factors that prompt customers to use VAs. We considered three customer characteristics (competence, habit, and trust), three VA perceptions (anthropomorphism, performance risk, privacy risk), and four characteristics describing the shopping occasion (available support, price value, susceptibility to social influence, and perceived social presence during the shopping encounter).

Examining the overall effects of our SEM (Web Appendix K), we identify the strongest effects for shopping occasion perceptions price value and available support, followed by the customers' susceptibility to social influence and their perception of the VA's anthropomorphism. The effects of customers' perceived risk of the VA not functioning as expected (performance risk), their trust in the technology, and their competence to utilize the technology also are significant but weaker. These insights clarify that all the antecedents included in our conceptual framework matter, even if they vary in relevance. Extant meta-analyses have not examined such effects for VAs (Web Appendix A), with the exception of Blut et al.'s (2021) work, focused on one specific antecedent (anthropomorphism). That meta-analysis combined virtual and embodied assistants, such that only 11 of the 108 samples pertained to VAs. Scholars studying VAs thus can use our framework to understand a broad set of antecedents, with strong predictive power.

4.2. Which cognitive and emotional responses do antecedents trigger in customers?

We assessed mediating effects to understand the processes by which antecedents influence technology use (Web Appendix K). The meta-analysis clarifies which relationships are well established and do not need further investigation, as well as which ones deserve more attention. Multiple antecedents notably exert indirect effects through both cognitive and emotional responses, including the perception of the VA's anthropomorphism as well as shopping occasion characteristics such as available support, price value, and susceptibility to social influence. The findings also particularly stress the strong indirect effects of negative emotions, suggesting the need for more scholarly attention. For example, researchers might consider the influence of negativity biases, such that customers tend to value positive information less than negative information (Chen and Lurie 2013). Few antecedents display indirect effects exclusively through just cognitive or emotional responses. The exception of performance risk perceptions is notable: They operate through emotions rather than cognitive responses, indicating that customers appraise the risk of the VA not functioning as expected as particularly relevant for their well-being and then express strong emotional responses (Bagozzi et al. 1999). Studies that neglect such mediating effects likely underestimate the importance of different antecedents. Furthermore, competence is the only antecedent that exerts direct, rather than indirect, effects on technology use, indicating that a customer's competence to utilize the VA predicts their use behavior. This finding deserves more investigation, perhaps through qualitative studies. Overall, we find more support for theories that anticipate indirect effects, like the TAM (Venkatesh and Bala 2008) and environmental psychology (Mehrabian and Russell 1974), than for those that propose direct effects, such as the unified theory of acceptance and use of technology

Table 6
Key findings and managerial implications.

Key findings and theoretical implications	*Managerial implications*
Which Factors Lead Customers to Use VAs?	
• Customer characteristics, VA perceptions, and shopping occasion perceptions influence use.	• *Focus on customer characteristics, technology perceptions, and situation in customer segmentation, marketing communication, and customer journey management.*
• Price value and support show strong total effects, followed by social influence, anthropomorphism, performance risk, trust, and competence.	• *Although all antecedents matter, managers should prioritize the allocation of their financial budget based on our empirical findings (e.g., invest in human telephone support first).*
• Antecedents proposed by the unified theory of acceptance and use of technology and related extensions are valid for research on drivers of VA use.	• *Managers can use our framework to measure and manage the VA introduction process (e.g., define related performance metrics and KPIs).*
Which Cognitive and Emotional Responses Do Antecedents Trigger in Customers?	
• Anthropomorphism, support, price value, and social influence exert indirect effects through both cognitive and emotional responses.	• *Managers should assess not only customers' cognitive judgments of the VA but also the emotions that customers experience (e.g., customer surveys and AI to track emotions in written text).*
• We find more support for theories suggesting indirect effects (TAM, environmental psychology) than direct effects (unified theory of acceptance and use of technology); emotion-based models of VA use should complement cognition-based ones.	• *Managers should adopt our framework or develop their own, considering customers' cognitive and emotional responses (e.g., define action plan for each of the framework's elements).*
• We observe strong indirect effects through negative emotions; scholars should use research on negativity bias to expand understanding of these effects.	• *Managers need to track the negative emotions induced by VAs and intervene where necessary (e.g., via Amazon Alexa's sentiment analysis).*
• Only a few antecedents display indirect effects exclusively through either cognitive (trust) or emotional (performance risk) responses.	• *For decisions regarding VA introductions, managers must reflect on their impact on both customers' cognitive and emotional responses.*
Which VA Types Enhance/Weaken the Effects of Antecedents and Responses?	
• Intelligence moderates the effects of antecedents on cognitive/emotional responses; it moderates the effects of emotional responses on intentions, but not cognitive.	• *To leverage the effects of different acceptance drivers, managers should recognize there is no one-size fits-all approach and employ multiple, different VAs.*
• Intelligent VAs not only display beneficial effects but also can engender adverse effects.	• *They should consider the four VA types (i.e., intelligence, task, modality, avatar) when selecting a VA for their firm.*
• Differentiate VAs that differ in intelligence and model such moderating effects when studying VA use.	• *Managers should consider the specific customer responses they want to enhance and translate into use.*
• Task type displays few moderating effects: one effect of antecedents on cognitive responses, but more effects on emotional responses. • Task type weakens the effect of emotional responses on intentions, but not cognitive.	• *To enhance ease-of-use perceptions, managers should select VAs that are intelligent, for noncommercial tasks, are text-based, and use avatars (e.g., VAs based on Chat GPT technology).*
• Commercial tasks are risky financial situations, though customers seem accustomed to using them. • Extend various acceptance models and consider moderating effects of task of the VA.	• *To enhance usefulness perceptions, managers should select simple VAs (e.g., rule-based chatbots) that rely on text-based communication (e.g., Google Dialogflow).*
• Modality moderates the effects of antecedents on cognitive and emotional responses; text-based VAs weaken the effect of cognitive responses on intention, but not emotional.	• *To enhance positive emotions, managers should favor intelligent VAs for noncommercial tasks that are voice-based and use avatars (e.g., Replika).* • *To reduce negative emotions, managers should select VAs that do not use avatars.*
• Use qualitative interviews to uncover explanations for the observed differences in our study. • Text-based communication leverages the effects of antecedents more often than voice-based.	• *To enhance translation of cognitions and emotions into technology use, managers should select VAs that are simple, for noncommercial tasks, that rely on voice-based communication and do not use avatars.*
• Avatar use shows mixed moderating effects, with no dominance of different antecedents; it enhances effects of emotional responses on intentions, but not cognitive.	
• Studying more avatar design appears promising (e.g., form, style, behavior, metaphors).	
• Extend different acceptance models and consider moderating effects of avatar use.	

(Venkatesh et al. 2012). However, relying on a single theory also appears insufficient to understand all the responses triggered by different antecedents. Emotion-based models of VA use should complement cognitive-based approaches, as in our meta-analytic framework; scholars might adopt and extend this framework further by incorporating other untested mediators or more differentiated measures of emotions.

4.3. Which va types enhance/weaken the effects of antecedents and responses?

With some unprecedented tests, we explore the influence of VA types on the impacts of both different antecedents on customer cognitions and emotions and the cognitions and emotions on technology use. By thus advancing VA theory, the findings help clarify why some antecedents display strong effects for some VAs but not others (Tables 5 and 6). We also explore the influences of four major VA types.

First, we observe the most differences from our comparison of *intelligent* versus *less intelligent VAs*, emphasizing the importance of this feature from a customer perspective. Because of their advanced capabilities, intelligent VAs enhance various relationships between shopping occasion perceptions (available support, perceived social presence) and ease of use. They also strengthen the effects of the perceptions of the VA (performance and privacy risk) and the shopping occasion (available support) on usefulness. This moderator matters for emotional responses too: It enhances the effect of habit on positive emotions suggesting that the sophisticated capabilities of intelligent VAs to facilitate emotion formation (Huang and Rust 2021) intensify the positive emotions generated by a customer's habitual use of a VA. Intelligent VAs also amplify the effects of customer characteristics (competence to utilize the VA), VA perceptions (anthropomorphism), and shopping occasion perceptions (available support) on negative emotions. Moreover, the influences of emotional responses (positive and negative emotions) on technology use are moderated, reiterating the importance of emotions in AI usage. Interestingly, intelligent VAs weaken the effects of social presence on usefulness and negative emotions too. Thus, the enhanced emotional capabilities of VAs appear unable to foster social bonding or mitigate negativity; instead, they display opposite effects. Our observation that positive emotions display weaker effects on behavioral intentions for intelligent VAs warrant more qualitative research to explain them.

With regard to VA theory, it is important to note that intelligent VAs may have beneficial effects but also can engender algorithm aversion or AI anxiety (Castelo et al. 2019; Li and Huang 2020). Scholars need to differentiate VAs accordingly, such that they must address intelligence when designing studies and testing for antecedents but also include the moderating effects in comparisons of different VAs. These moderating effects exert influences not only in the relationships between antecedents and cognitive and emotional responses but also in the translation of emotional responses into use. Applying our proposed framework and moderators, scholars also might assess whether these effects hold for next-generation AI that focus even more strongly on feeling intelligence (Huang and Rust 2022).

Second, we find differences between *commercial and noncommercial VAs*, such that those performing commercial tasks enhance the effects of VA perception (privacy risk) on ease of use. This suggests that in commercial settings customers exhibit greater risk-aversion (Gashami et al. 2014) and thus the perceived risk of losing control over their data greatly contributes to their discomfort with the VA. This moderator also weakens the effects of some customer characteristics (habit of using the VA) and shopping occasion perceptions (available support) on positive emotions, but the effects of other shopping occasion perceptions (social influence) appear enhanced. It also weakens the effect of positive emotions on behavioral intentions. Commercial tasks, such as purchasing through a chatbot, seemingly are perceived as riskier (Gashami et al. 2014), but because investigations of these moderating effects are limited, we call on scholars to apply qualitative methods and identify the reasons for the observed differences.

With regard to VA theory, the relatively few significant differences for this moderator seem to imply that customers have grown accustomed to engaging in commercial transactions using VAs, and they consistently factor in the associated risks. They also seem to have developed strategies for coping with potential financial losses. Scholars might explore whether the effects of this VA type differ more prominently in infrequently purchased product categories, in which customers have less experience, or that are rather expensive. Additional cross-context theorizing and extensions to the existing TAM might incorporate the moderating effects of these and other tasks performed by the VA. Furthermore, the commercial character of VA appears particularly promising for revealing the impacts of antecedents on positive emotions, and then when these emotions translate into use. Other tasks could moderate the effects of the antecedents on cognitive responses instead.

Third, the differences we observe for *voice*- versus *text-based VAs* align with human–computer interaction research that suggests differences in information production, transmission, and reception between voice and text (Rzepka et al. 2022). Voice-based VA weaken the impact of shopping occasion perceptions (available support, price value, and perceived social presence) on cognitive responses; suggesting that shopping context characteristics appear less important when the voice-based VA exerts its effective persuasive capabilities (Ischen et al. 2022). Moreover, voice-based communication weakens the effects of some VA perceptions (anthropomorphism) on ease of use, but it strengthens the effects of performance risk, the customer's perceived risk of the VA not functioning as expected. It also weakens the effects of one shopping occasion perception (price value) on positive emotions, but strengthens the effects of customer characteristics (competence) and other shopping occasion perceptions (social influence). Voice-based VAs strengthen the effects of cognitive responses (usefulness) on use too, though not emotional responses. Price value diminishes in strength for driving positive emotions for voice-based VAs. Thus, it seems that these VAs enhance emotional transmissions only for certain antecedents (Sailunaz et al. 2018), and the distinction requires more scholarly attention. We also find a stronger relationship between usefulness and use for voice-based VAs; perhaps customers develop greater expectations of these VAs' performance, and then cognitive responses gain importance. Comparing these findings, voice-based VAs seem to weaken the effects of several beneficial antecedents and enhance the effects of adverse antecedents. More qualitative research is needed to better understand these and other moderating effects.

In terms of theory implications, our meta-analysis reveals that text-based communication can leverage the effects of antecedents better than voice-based, particularly for cognitive responses (Ischen et al. 2022). Text-based VAs lead to more positive perceptions because the benefits of speaking to VAs—including less cognitive effort and physical exertion due to the hands-free operation (Kock 2004)—are surpassed by the greater interaction speed of text-based conversations (Le Bigot et al. 2004). Therefore, researchers need to align their conceptual models and consider such moderating effects when studying different VA types. They might identify task differences and the products for which voice-based VAs excel. Also, more research is needed to determine when the modality of the VA informs the influence of antecedents on negative emotions; we observed no such differences.

Fourth, the comparison of *avatar-* versus *non-avatar-based VAs* reveals mixed results, with no clear dominance. Avatar-based VAs enhance the effects of one customer characteristic (competence) and one shopping occasion perception (social presence) on ease of use; they weaken the effect of another shopping occasion perception (price value). They enhance the effects of one customer characteristic (competence) on usefulness. The results for emotional responses are also mixed. Avatar-based VAs enhance the effects of customer characteristic (competence) on positive emotions but weaken the effect of VA (performance risk) and shopping occasion (price value) perceptions. Similarly, they enhance the effects of VA perceptions (anthropomorphism) on negative emotions, suggesting that these VAs are more noticeable through their animated and vivid appeal (Bartneck et al. 2009), but weaken the effects of shopping occasion perceptions (social presence).

Finally, they enhance the effects of emotional responses (negative emotions) on behavioral intentions but not the effects of cognitive responses. Avatar-based VAs strengthen the effect of social presence on ease of use too, such that by signaling the perceived “socialness” of the VA, avatars may make them easier to use. Scholars should build on this and related findings to explore the reasons for the observed differences.

These findings advance VA theory by providing initial insights into the specific antecedents for which avatar uses might be most meaningful. In turn, they should be added to extended TAMs that acknowledge the moderating effects of avatar use. Researchers could differentiate further types of avatars, as suggested by emerging avatar marketing theory that identifies variations in form (e.g., 2D/3D, static/dynamic, gender), style (e.g., photorealistic, comic-like), behavior (e.g., verbal/nonverbal interaction, scripted/natural), and metaphors (human/zoonotic/functional). Other tests of VA types might consider their precise impacts on the relationships between antecedents and usefulness.

4.4. Managerial implications

The implications of this meta-analysis for managers pertain to the factors that prompt customers use VAs, triggered cognitive and emotional responses, and VA type selection (Table 6). In terms of key influences, managers should note the relevance of different customer characteristics, VA perceptions, and shopping occasion perceptions. Price value and support exert the largest total effects, followed by social influence, anthropomorphism, performance risk, trust, and competence. Even if all antecedents matter, retailers should allocate their financial budgets in accordance with our findings.

Regarding *customer characteristics*, retailers should assess and consider the technological competence of their customers, as well as whether those customers trust the technology. Retail managers can use these two criteria for customer segmentation and then introduce VAs to more competent customer segments first. Additionally, they can proactively improve customers’ proficiency in using the technology, for example by providing tutorials on how customers should interact with chatbots, such as appropriate ways to phrase questions to ensure the chatbot comprehends their requests. Furthermore, retailers need to manage customers’ *VA perceptions* and stress humanlike attributes as part of their communication, such as assigning the chatbot a human name or enabling the voice assistant to speak with a voice that sounds like an average person. Along with ongoing monitoring of customer risk perceptions, managers can alleviate perceived risks by offering money-back guarantees or stressing quality cues like the retailers’ brand. For *shopping occasion perceptions*, we recommend that managers offer sufficient support and resources to facilitate VA interactions, such as when Amazon Business offers human telephone support alongside its chatbot services. Other resources, such as FAQs and illustrative step-by-step instructions, can help customers feel supported too. In this assessment, managers should note the customer costs of using VAs and address them. Finally, it may be helpful to stress social norms for interactions and embed VAs in or link them to social media (e.g., Facebook). They can apply our proposed framework as a guideline for both measuring and managing VA introduction processes.

Beyond customers’ cognitive judgments, managers need to acknowledge the emotions that customers experience during interactions with VAs, as represented in our conceptual framework. Regarding ease of use and usefulness perceptions, retailers should stress these benefits when promoting the VA, as when the eBay ShopBot claims that interacting with it is as effortless as chatting with a friend. Regarding emotions, managers should monitor them with customer surveys but also use natural language processing and AI to track customers’ expressions of positive and negative emotions in written text and verbal conversations. They need particularly to consider the negative emotions induced by VAs, considering their strong influence on technology use. Because AI-based assistants (e.g., Amazon Alexa) can use sentiment analysis to assess customers’ current emotional conditions, according to their tone of voice, we suggest that retailers engage in real-time monitoring to intervene the very moment that customers experience distress.

Finally, when selecting a VA to introduce, managers can leverage the effects of different acceptance drivers. There is no one-size fits-all approach; VAs’ performance inevitably varies across customer responses. Thus, multiple VAs might be necessary. Table 7 details which VAs we recommend for enhancing which customer responses and then translating them into use. For example, to intensify the effects of antecedents on *ease-of-use* perceptions, retailers should select intelligent VAs for noncommercial tasks, with text-based communication and avatars. Many existing AI-powered chatbots like Chat GPT or Bard reflect this approach and exploit a wide range of AI technology, including machine learning, natural language processing, and sentiment analysis. Managers also might enhance *usefulness* perceptions by selecting simple VAs (e.g., rule-based chatbots) that rely on text-based communication, which they can use for any type of task and with or without an avatar. For KLM

Table 7
Recommended VAs by response type and outcome.

IV	DV	Intelligent/Less intelligent	Commercial/Noncommercial	Voice/Text	Avatar/No avatar
Enhancing cognitive responses					
Competence	Ease of use				Avatar
Anthropomorphism				Text	
Performance risk				Text	
Psychological risk			Noncommercial		
Support		Intelligent		Text	
Price value					No avatar
Social presence		Intelligent		Text	Avatar
Competence	Usefulness				Avatar
Performance risk		Less intelligent			
Privacy risk		Less intelligent			
Support		Intelligent		Text	
Price value				Text	
Social presence		Less intelligent			
Enhancing emotional responses					
Competence	Positive emotions			Voice	Avatar
Habit		Intelligent	Noncommercial		
Performance risk					Avatar
Support			Noncommercial		
Price value				Text	No avatar
Social influence			Commercial	Voice	
Competence	Negative emotions	Intelligent			
Anthropomorphism		Less intelligent			No avatar
Support		Intelligent			
Social presence		Less intelligent			No avatar
Translating cognitions/emotions into technology use					
Positive emotions	Behavioral intention	Less intelligent	Noncommercial		
Negative emotion					No avatar
Usefulness	Use			Voice	
Negative emotion		Less intelligent			

Airlines, Google Dialogflow built simple conversational flows; these chatbots require less data and training to produce useful responses. To enhance customers' *positive emotions*, managers should favor intelligent VAs; VAs for noncommercial tasks that are voice-based and use avatars also are likely to enhance positive emotions. Although VAs without avatars appear promising for reducing *negative emotions*, we lack any clear indication of how other VA types might inform such responses. Finally, managers interested in *translating cognitions and emotions* into increased technology use should select rather simple VAs for noncommercial tasks, relying on voice-based communication and avoiding avatars.

4.5. Research agenda

The meta-analysis suggests an agenda for continued research into the antecedents of VA use, VA-related cognitions and emotions, and VA types (Table 8). This agenda reflects not only our meta-analytic findings but also its limitations and some underresearched areas.

Beyond exploring the impact of different antecedents on VA use, scholars could continue to uncover the influences of novel customer characteristics in the VA context. For example, Blut et al. (2022) propose the relevance of personality traits, such as personal innovativeness. It also may be worth studying other VA perceptions. We explore the role of risk perceptions, but in addition, the information privacy paradox (i.e., people often share private information despite privacy concerns) could provide a novel perspective and suggest further antecedents. In terms of other shopping occasion perceptions, as Gelbrich et al. (2021) note, VAs might provide both instrumental and emotional support to customers.

With regard to the mediating effects of customers' cognitive and emotional responses and which antecedents relate to them, we call for tests of antecedents of different types of emotions (e.g., fear, anger, joy, sadness, disgust, surprise). A plethora of emotions can be induced by VAs and should be tested explicitly; for example, disgust and sadness determinants may differ. Also, more research is needed into the cross-over effects of different antecedents, such as how other antecedents cited by cognition-based TAM might influence emotions, or how antecedents from emotion-based theories can influence cognitions. Broader types of outcome variables also might be studied, to determine how induced cognitive responses and emotions influence technology use but also revenues, sales, cross-buying, brand perceptions, and online shopping experi-

Table 8
Research agenda on antecedents of VA use, cognitive and emotional responses, and VA types.

Issue	Exemplary research directions
Customer characteristics, VA perceptions, and shopping occasion perceptions	➢ Assess the influence of further customer characteristics, such as personality traits (e.g., personal innovativeness; Blut et al. 2022). ➢ Explore underresearched VA perceptions; theories like information privacy paradox may suggest further antecedents that are related to privacy concerns and the risk of sharing information. ➢ Test further shopping occasion perceptions, such as instrumental and emotional support to customers (Gelbrich et al. 2021) or VA personality (e.g., Big 5 trait model used for human can be applied to VAs)
Cognitive and emotional responses	➢ Test antecedents for different emotions (e.g., fear, anger, joy, sadness, disgust, expectancy, surprise); a plethora of emotions can be induced by VAs, and the determinants likely differ. ➢ Assess cross-over effects; explore which antecedents discussed in cognition-based acceptance theories influence emotions, and which antecedents from emotion-based theories influence cognitions. ➢ Explore the impact of cognitions and emotions induced by VAs on further outcomes relevant to retailers; determine the relative importance of both for driving cross-buying, brand perception, or online shopping experience. ➢ Assess how cognitions and emotions influence store-level outcomes (e.g., sales, profitability) and employee-level outcomes (e.g., role stress, efficiency). ➢ Explore the stability of feelings; the literature differentiates between emotions and moods, recognizing that moods last longer; it would be interesting to explore the stability of feelings induced by VAs.
VA types and context differences	➢ Differentiate avatars based on form (e.g., 2D/3D, static/dynamic) and behavior (e.g., interactivity) according to emerging avatar theory; assess when avatars exert main effects on anthropomorphism. ➢ Examine how ChatGPT or Bard could enhance VAs use in a retail context; explore the data requirements that AI-based VAs need to provide services in retailing ➢ Explore the performance of hybrid VAs that combine service provision through VAs and human chat; the complexity and high traffic volume may negatively affect the customer experience. ➢ Explore how customer characteristics such as personality traits impact the appraisal of encounters with VAs. ➢ Test theoretically meaningful contextual moderators; scholars may explore the differing role of VA types at different stages of the customer journey (search, purchase, post-purchase). ➢ Assess the moderating role of different retail formats and assortments; we compared retail versus service differences, but scholars should employ more detailed retail typologies to describe the VA context.

ences. For example, if a hotel room is not available for the location or dates a guest requests, Marriott Hotels' chatbot keeps them engaged by offering alternative options. Scholars could explore such outcomes in a retailing context, including whether and how ease of use or usefulness might drive them, relative to positive and negative emotions. Do negative emotions exert the strongest effect on these outcomes, as they do for technology use? Do they increase customers' likelihood to overspend? In addition, research into the stability of such feelings would be helpful. Prior literature differentiates between emotions and moods; moods last longer. Longitudinal studies should explore the time-stability of these feelings.

On the basis of our novel investigation of the moderating effects of different VA types, we recommend that scholars extend the findings and test additional, theoretically meaningful moderators. Such investigations might include sophisticated VAs, such as ChatGPT or Bard, in actual retail contexts. Although these VAs are capable of providing compelling responses, the accuracy of their answers is not guaranteed, and more research is needed into how customers respond. Noting the difficulty of training VAs that rely on machine learning, scholars also should explore the data requirements for providing different services, as well as the performance achieved by hybrid tactics that combine VA service provision with human chat options. As we noted previously, customer characteristics such as personality traits might influence appraisals of encounters with VAs, but such moderating effects are difficult to assess in meta-analyses. Customers who are prone to reactance behavior might respond with negative emotions if friends and family urge them not to use VAs. Furthermore, VAs perform distinct roles at different stages of the customer journey (search, purchase, postpurchase); the online retailer Bol.com uses its chatbot to answer customers' product questions, guide them through the shopping journey, and then facilitate returns. Scholars also could assess the moderating roles of other, more detailed retail classifications, including how VAs respond to more complex shopping contexts (e.g., for electronics versus groceries).

Finally, VA technology remains a new and thriving field of research. Our meta-analysis provides some new insights and may guide further research efforts. We hope scholars and retailers find these recommendations inspiring, considering how AI has advanced VA technology and how many more retailers plan to introduce such assistants.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jretai.2024.04.001.

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