HUMAN-MACHINE COMMUNICATION

Human-Machine Communication
Volume 8, 2024
https://doi.org/10.30658/hmc.8.5

The Impact of Human-AI Relationship Perception on Voice Shopping Intentions

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Abstract

In the emerging field of voice shopping with quasi-sales agents like Amazon's Alexa, we investigated the influence of perceived human-AI relationships (i.e., authority ranking, market pricing, peer bonding) on (voice-)shopping intentions. In our cross-sectional survey among experienced voice shoppers ($N = 423$), we tested hypotheses specifically differentiating voice shopping for low- and high-involvement products. The results emphasized the importance of socio-emotional elements (i.e., peer bonding) for voice shopping for high-involvement products. While calculative decision-making (i.e., market pricing) was less relevant, the master-servant relationship perception (i.e., authority ranking) was important in low-involvement shopping. An exploratory analysis of users' desired benefits of voice shopping reinforces our claims. The outcomes are relevant for conversation designers, business developers, and policymakers.

Keywords: voice shopping; human-AI relationship; conversational AI; high- and low-involvement; perceived benefits

Introduction

With the introduction of online shopping, people could purchase almost anything with a few clicks. Three decades later, people can just *tell* a computer to place an order. Although voice shopping is a form of e-commerce, it substantially differs from traditional online shopping (Klaus & Zaichkowsky, 2022). We argue that voice shopping with a conversational

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ISSN 2638-602X (print)/ISSN 2638-6038 (online)
www.hmcjournal.com

artificial intelligence (AI) is conceptually more similar to decision-making in a brick-and-mortar store involving in-person interactions with human salespeople and should be investigated as such.

Research on relationships between the consumer and (human) seller is popular in the marketing literature (Alvarez & Fournier, 2016). For example, studies have shown that a positive seller-buyer relationship leads to greater brand trust and more positive affect by consumers (Carroll & Ahuvia, 2006; Chaudhuri & Holbrook, 2002). But the relationship perspective has yet not been translated into human-AI interaction, investigating the perception of conversational AI as quasi-sales agents whom consumers form some sort of relationship with (e.g., Lim et al., 2022; Ramadan, 2021; Rhee & Choi, 2020). In fact, research precisely on human-AI relationships is, in general, still nascent (Pentina et al., 2023), and the few existing findings paint a complex picture.

Hu et al. (2022) found that people who see their conversational AI mostly as assisting them have stronger voice shopping intentions, motivated by a hierarchical power experience over their voice assistants, a claim supported by Tassiello et al. (2021). While Hu et al. (2022) did not differentiate what users bought, Tassiello et al. as well as Rhee and Choi (2020) did. Both used the concept of low- and high-involvement: Low-involvement products are characterized as low-cost items consumers tend to consider without extensive deliberation, in contrast to high-involvement products, which are typically pricier and necessitate thorough evaluation (Mari & Algesheimer, 2021; Rhee & Choi, 2020; Tassiello et al., 2021). In the development of their hypotheses, they argue that shoppers think differently about the products, requiring different persuasive messages to facilitate voice shopping. Contrasting Hu et al.'s (2021) and Tassiello et al.'s (2020) findings, Rhee and Choi (2020) found that a friend-like voice shopping user interface increased voice shopping intentions for low-involvement products.

These partly inconsistent findings call for further research, including the nature of the perceived relationship and the purchase. Therefore, we apply a multidimensional human-AI relationship model while differentiating between low- and high-involvement products. Assuming that users perceive their relationship to their conversational AI not just along a friend or servant dimension but along several dimensions, as suggested by Tschopp et al. (2023), holds promise in gaining differentiated insights into users' voice shopping behavior and addressing the contradictions in the current landscape. Thus, the focal question of this study is: Does the way users relate to their conversational AI influence what kind of products they buy?

How Users Perceive Their Relationship to Conversational AI

The remarkable progress in AI in the past decades has steadily stretched the boundaries of human-AI interaction and communication, demonstrated by the developments of language models. These advancements have rendered users' interactions not only social in the sense of being imbued with meaning or emotion but have also expanded the potential for the establishment of what might be considered relationships with AI agents, as asserted by Pentina et al. (2023).

To examine the human-AI relationship perception from a multidimensional perspective, we are building upon Tschopp et al.'s (2023) adaptation of the Relational Models

TABLE 1 Description of the Three Modes of Human-AI Relationships (based on Tschopp et al., 2023)

Peer Bonding	Market Pricing	Authority Ranking
► Most human-like dimension where the user treats the conversational AI as an equivalent peer. ► Best characterized as a communal relationship.	► The user perception is guided by cost-benefit analyses with no hierarchies. ► Best characterized as an exchange relationship on *eye level*.	► A hierarchical order is perceived between users and the conversational AI. ► Best characterized as a master-servant relationship.
The user tends to feel emotionally closer to the system.	The user tends to care about competence and rational trust in the system.	The user tends to use the system for a greater variety of purposes.

Theory (RMT) by Alan P. Fiske (Haslam & Fiske, 1999) to human-AI relationships. RMT is a theory on how humans construe their relationships with other humans. RMT describes four dimensions and has received mighty empirical support in the past decades. These four dimensions are (1) communal sharing (i.e., a kinship-like relationship as it is with families based on mutual trust), (2) equality matching (i.e., a tit-for-tat-like relationship as with roommates in a shared flat where equal give-and-take is key), (3) authority ranking (i.e., a hierarchical relationship characterized by a clear chain of command like soldiers and their superiors), and (4) market pricing (i.e., a currency-based relationship characterized by cost-benefit analyses as it is with employers and their bosses in a workplace).

Applying RMT, Tschopp et al. (2023), found that human-AI relationships are perceived along three dimensions varying in emotional breadth and perceived agency. Communal sharing and equality matching merged into one emotional dimension named peer bonding (see Table 1). They found that conversational AI users characterized their relationship mostly by authority ranking (i.e., a hierarchical owner-assistant relationship) and market pricing (i.e., a nonhierarchical exchange relationship) and least by peer bonding (i.e., a peer-like relationship). Notably, authority ranking was not informative for variables concerning system perception (e.g., trust, perceived intelligence, or affinity to technology). The two rather interactive dimensions (i.e., market pricing and peer bonding) had stronger predictive values, especially regarding anthropomorphism (Tschopp et al., 2023), which drives the development of our hypotheses and research questions.

While the initial work by Tschopp et al. (2023) remained exploratory, we aim to further investigate their assumptions in an applied context, namely voice shopping. This context presents an intriguing opportunity because multiturn dialogues are necessary to make a purchase decision. In other words, you have to actually communicate with the conversational AI and not only give orders, such as turning off the lights, where other relational dynamics may be involved.

Peer bonding, often regarded as the most emotionally charged connection, involves regarding the partner as an equal and companion-like figure while also upholding a sense of responsibility for one's conduct (Tschopp et al., 2023). Arguably, for people who see their device through this relationship mode, the voice shopping experience would be more like shopping with a peer.

The newly introduced perception of conversational AI as a rational exchange partner, called market pricing, was found to be rather popular (Tschopp et al., 2023). Its core characteristic lies in the reliance on ratio values, devoid of hierarchies, thus resembling an equal-other, granted some sort of agency. Arguably, for people who see their device through this relationship mode, the voice shopping experience would be more like having a professional sales agent making the shopping decision together with the consumer.

The majority of respondents perceived their devices as authority ranking. The key characteristic of this arrangement is the creation of a linear hierarchy between humans and the conversational AI. For people who see their device through this relationship mode, the shopping experience would be more like shopping with a subservient helper or concierge. However, before making such assumptions, a better understanding of voice commerce is necessary.

Shopping via Conversational AI

Voice shopping, or voice commerce, is an emerging commercial trading system where, for instance, Alexa users (Amazon's conversational AI) can search, purchase, and track products on Amazon solely through a voice user interface (VUI) (Halbauer & Klarmann, 2022; Ramadan, 2021). Alexa shoppers predominantly purchase entertainment products (such as music or books), household essentials (like batteries or toilet paper), and clothing, whereby re-purchases and new orders occur with equal frequency (for a comprehensive breakdown of product categories, see Kinsella, 2018). Practitioners are eager to leverage this new sales channel. However, research in the field is in its infancy, with limited empirical data on what promotes or hinders voice shopping scattered across disciplines (Klaus & Zaichkowsky, 2022; Lim et al., 2022).

From a psychological perspective, initial studies have investigated what drives voice shopping intentions. Trust (Huh et al., 2023; Mari & Algesheimer, 2021), perceived human-likeness/anthropomorphism (Han, 2021; Huh et al., 2023), perceptions of social presence, emotional bonding, and para-social interaction and dialogue (Ramadan, 2021), were found to have a positive influence on voice shopping intentions and continuance. These studies stress the importance of the social dimension in voice purchasing behavior. Especially with regard to the voice shopping process, the increasing interactive verbal decision-making processes and two-way interaction render "voice assistants partners in the decision-making dialogue rather than mere order takers" (de Bellis & Venkataramani Johar, 2020; Dellaert et al., 2020)

Furthermore, only a limited number of empirical studies have distinguished voice shopping intentions based on the specific products individuals purchase, which likely engage distinct processes as comprehensively laid out by Rhee and Choi (2020). In simpler terms, it is highly likely that there is a notable distinction between buying batteries and purchasing a laptop through voice commands, where there is limited access to information and a varying necessity to rely on the AI as a sales agent.

When using conversational AI for product selection, Klaus and Zaichkowsky (2022) suggest that the algorithm serves distinct purposes based on the complexity and functionality of the product. In their model, they differentiate high- and low-involvement situations, where the algorithm serves different functions depending on whether the product is simpler and more functional (i.e., low-involvement). This entails a more utilitarian approach, where users allow the conversational AI to handle the purchase. This concept was also applied in a study by Mari and Algesheimer (2021), who selected batteries as a low-involvement product, invoking the "yeah, whatever" heuristic. In contrast, the decision-making process for intricate, costly, and/or high-risk products, as outlined in Klaus and Zaichkowsky's model, appears quite different. When acquiring items like a $500 vacuum cleaner, more information and guidance are necessary, making them high-involvement purchases that demand greater time and effort for decision-making. In this framework, an algorithm aids the buyer in making the most informed shopping decision collaboratively.

Against this background and given the inclination of people to respond to technological systems in social ways (Nass & Moon, 2000) and the empirical importance of the social dimensions as antecedents of (voice) shopping decisions, it is rather surprising that only a few studies have looked at the impact of perceived relationship to the conversational AI on home shopping behavior. Much research has focused on relational proxies, assessing constructs such as perceived warmth, psychological distance, or anthropomorphism (e.g., Gong, 2008; Pitardi & Marriott, 2021) or role ascriptions (e.g., Sundar et al., 2017). Furthermore, and as mentioned above, inconsistent results raise further questions: Hu et al. (2022) have found that presenting conversational AI as servants enabled a power experience for users as masters and increased voice shopping intentions (given that they had a desire for power). Similarly, an experimental study by Tassiello et al. (2021) found that the subservient assistant role facilitated voice shopping. On the other hand, Rhee and Choi (2020) found that a friend-like social design had a positive influence on voice shopping intentions. Notably, this was particularly important for buying low-involvement products. These findings underscore the need for further research to carefully examine and dissect voice shopping intentions, particularly by distinguishing between different types of products that involve varying levels of involvement in the purchase decision-making process.

Hypotheses Development

Does the Perceived Human-AI Relationship Influence Voice Shopping Intentions?

Dellaert et al.'s (2020) argument that virtual assistants serve as partners in decision-making suggests that peer bonding and market pricing are highly relevant for voice shopping, more so than authority ranking. To reiterate, a large amount of research suggests that human-like system perception variables such as perceived human-likeness (Huh et al., 2023) or emotional bonding (Ramadan, 2021) are promoting shopping intentions. We thus predict:

> **H1:** Higher values in peer bonding predict a stronger intention to use voice shopping.

Market pricing, the non-hierarchical relationship dimension characterized by exchange and interaction, is emotionally less pronounced. However, market pricing still constitutes a human-like relationship, in the sense that it requires that users attribute agency to the system and see their conversational AI rather as an exchange partner whom they meet on "eye level" than as a tool. Relying on the fact that human-like perceptions of conversational AI go hand in hand with voice shopping intentions (Huh et al., 2023), we also expect:

H2: Higher values in market pricing predict a stronger intention to use voice shopping.

Based on the rationale that the conversational AI functions as a sales agent rather than a simple order processor, and considering the absence of predictive information regarding authority ranking as per Tschopp et al.'s study (2023), we posed the influence of authority ranking as an exploratory research question in our preregistration. The results were analyzed in an equitable manner within our results section.

RQ1: How does authority ranking associate with general voice shopping intentions?

Different Predictors for Different Products?

We argue that different relationship dimensions will predict shopping intentions for different products because people evaluate products differently. Inspired by Rhee and Choi's (2020) arguments, this rationale is based on the elaboration likelihood model (ELM, Petty & Cacioppo, 1986), which distinguishes two routes. The *peripheral route* is characterized by a low amount of effort taken to process product information, but it could also be based on evaluating characteristics of the seller (see also Rhee & Choi, 2020). The peripheral route is typically used for low-involvement items, which are often cheap and interchangeable products (e.g., toilet paper or chewing gum; see Rhee & Choi, 2020). In other words, when a shopping decision bears no real risk, people do not think a lot but follow intuitions and emotions. This focus on intuition and emotions resonates with peer bonding, which is characterized by emotions and similar to a relationship with human peers whom people follow intuitively without much thought. This is in line with the study by Rhee and Choi that demonstrated the positive effect of a friend-like social design on shopping for low-involvement products but not for high-involvement products.

The *central route* is used for more cognitively demanding products. This form of information processing is characterized by careful elaboration of the quality of arguments, facts, or figures (Petty & Cacioppo, 1986). This cognitive effort is typically only invested when the motivation to process the information is high, in other words, in a shopping context in which more is at stake—financially or personally. This should apply in the case of high-involvement products. When voice shopping for high-involvement products, the decision-making process resembles the central route. Voice shoppers should be highly motivated to evaluate product characteristics and rationality should dominate in a "cost-benefits-analysis style." This style fits a market pricing relationship based on cost-benefit analysis. Taken together, the intuitive and emotional processing style applied when shopping low-involvement products resonates with peer bonding, whereas the cost-benefit-analysis style applied when buying high-involvement products resonates with market pricing (see Table 1). We thus predict:

H3: The intention to buy low-involvement products via voice shopping is predicted to a stronger extent by peer bonding than by market pricing.

H4: The intention to buy high-involvement products via voice shopping is predicted to a stronger extent by market pricing than by peer bonding.

As before, we posed an exploratory question regarding the role of authority ranking:

RQ2: How does authority ranking associate with voice shopping intentions for low- and high-involvement products?

To situate the relational approach into common customer value frameworks, we assessed what people care about in voice shopping. We looked at desired hedonic, utilitarian, symbolic, and social benefits (inspired by McLean & Osei-Frimpong, 2019) and how they associate with voice shopping intentions and human-AI relationships. We anticipate that the exploratory analysis will provide conceptual reinforcement for our findings. Given the early stage of the field, it is premature to make definitive predictions and thus commit to the exploration of our research question.

RQ3: How do desired shopping benefits associate with the human-AI relationship perception and voice shopping intentions?

Methods

Design and Participants

We conducted a preregistered cross-sectional study to test our hypotheses https://aspredicted.org/2pg28.pdf. The study was run online via Prolific in July 2022. We aimed at a sample of 450 based on the assumption that N = 250 is required for stable correlations (Schönbrodt & Perugini, 2013). We added 200 participants to definitely end up with N > 250, even in case of substantial exclusions. We preregistered the following exclusion criteria: no experience in voice shopping, failing at least one attention check, and too short (< 150 seconds) or too long (> 80,000 seconds) duration of the survey. In a prescreening, we surveyed people (N_{total} = 800) to identify potential participants engaging regularly in voice shopping with conversational AIs such as Alexa. We collected data from 451 participants fulfilling this criterion in exchange for £1.10. Twenty-eight participants were excluded based on the criteria mentioned above or because they were outliers with an absolute studentized deleted residual > 2.59 in the regression testing (H1 and 2), another preregistered exclusion criterion. The remaining respondents N = 423 (57% female, 42%, male, 1% other; age M = 41, SD = 11.4, age range 19–84 years) responded to the questionnaire regarding their use of Alexa (78%), Google Assistant (16%), Siri (5%), or other conversational AI (1%). More information about users' voice shopping preferences can be found in the supplement. A sensitivity analysis for a single predictor in multiple regression analysis with three predictors (the analysis for the main predictions) indicated that the sample size was sufficient to detect an effect of f^2 = .018 at alpha = .05 and 1-beta = .8.

Procedure

We invited participants to take part in a study on users' perceptions of voice shopping. After providing consent, participants had to choose which conversational AI their answers referred to and then respond to the human-AI relationship questionnaire (adapted from Haslam & Fiske, 1999; see Tschopp et al., 2023). The instructions for the measure require people to focus on a specific device when reporting their relationship. Afterward, we surveyed users about their shopping intentions to test the predictions. Variables were presented in a fixed order. All items were randomized. Next, exploratory variables were assessed. Perceived and desired benefits, trust, and user characteristics (device specifics, frequency of and experience in voice shopping, estimated voice shopping spending per year). We placed questions for demographic information and a final opportunity to withdraw their data at the end. Analyses have been conducted using SPSS 25.0 unless reported otherwise. Supplemental data, code, data, and pre-registration are available at https://researchbox.org/1029.

Measures

Human-AI relationship was assessed using the questionnaire by Tschopp et al. (2023). Administering the questionnaire involves a specific mandatory procedure. Responding to the Human-AI relationship questionnaire necessitates first choosing a voice assistant their answers refer to (e.g., Alexa or Google Assistant). After selecting their preferred assistant, participants were directed to reflect on past shopping experiences and rate the extent to which items described their relationship with the chosen assistant in mind. The questionnaire consisted of 17 items using a 7-point Likert scale (1 = *not at all true for this relationship*, 7 = *very true for this relationship*): nine items for peer bonding, four items for authority ranking, and four items for market pricing. A principal component analysis (PCA) with varimax rotation was conducted (see Table 2). The three factor solution (based on the Kaiser criterion) explained 56.42% of the variance. As in prior studies, the first component represents peer bonding, the second component authority ranking, and the third component market pricing. Due to high loadings (> .4) on a factor they were not intended to correlate with, we omitted items 6 and 17. The final scales presented sufficient reliabilities: *Cronbach's Alpha* = .91 for peer bonding, *Alpha* = .71 for authority ranking, and *Alpha* = .66 for market pricing. Market pricing was positively correlated with peer bonding ($r = .47$, $N = 423$, $p < .001$) and authority ranking ($r = .27$, $N = 423$, $p < .001$). No significant correlation was found between authority ranking and peer bonding ($r = -.09$, $N = 423$, $p = .073$).

Voice shopping. We measured the *general intention to continue voice shopping* with three items adapted from McLean and Osei-Frimpong (2019). Respondents indicated their agreement on a 7-point Likert scale (3 items, 1 = *strongly disagree* to 7 = *strongly agree*). For instance, "I plan to continue to use the conversational AI for shopping in the future." An index was formed by averaging the responses (*Cronbach's Alpha* = .98).

TABLE 2 Results From a Factor Analysis of the Human-AI Relationship Questionnaire ($N = 423$)

	Item	Factor Loading		
		1	2	3
Peer Bonding				
1	There is a moral obligation to act kindly to each other	**.550**		.387
2	Decisions are made together by consensus	**.771**		
3	You tend to develop similar attitudes and behaviors	**.756**		
4	It seems you have something unique in common	**.839**		
5	You two are like a unit: you belong together	**.784**		
6	You are like tit for tat: you do something and expect something similar in return	**.487**		.425
7	Everyone has an equal say when a decision is made	**.780**		
8	You take turns doing what the other wants	**.786**		
9	You are like peers or fellow co-partners	**.783**		
Authority Ranking				
10	One of us is entitled to more than the other		**.701**	
11	One directs the work, the other pretty much follows		**.675**	
12	You are like leader and follower		**.691**	
13	One is above the other in a kind of hierarchy		**.745**	
Market Pricing				
14	What you get from this interaction is directly proportional to how much you give			**.661**
15	You have a right to a fair rate of return for what you put into this interaction			**.733**
16	You expect the same return on your effort other people get			**.740**
17	Your interaction is a strictly rational cost-benefit analysis		**.536**	

Note. Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Rotation converged in five iterations. The highest factor loadings are in bold, factor loadings below .30 are not displayed.

Intention to continue voice shopping for low-involvement products and the *intention to continue voice shopping for high-involvement products* were assessed with a single item each on a 7-point Likert scale (1 = *strongly disagree* to 7 = *strongly agree*). Participants read the description, see Table 3, and rated their agreement "I predict I would continue to use the conversational AI for shopping in the future." General voice shopping intentions were highly correlated with low-involvement shopping intentions ($r = .81$, $N = 423$, $p < .001$) and moderately with high-involvement shopping intentions ($r = .41$, $N = 423$, $p < .001$). Using the three indicators is supported by a principal component analysis (see supplement).

TABLE 3 Description of Low- and High-Involvement Shopping Intentions

Intention to continue voice shopping for low-involvement products	Intention to continue voice shopping for high-involvement products
Think about your future voice shopping experiences. Would you use the voice assistant to shop for products, which are rather convenience products, that require no effort to buy, and there are no emotional values or risks attached? For example, products such as paper towels, chewing gum, cereals, or a specific book. Please rate the extent to which these statements describe your intention to continue purchasing these types of products with your voice assistant in the future.	Think about your future voice shopping experiences. Would you use the voice assistant to shop for products which are rather complicated and require some effort to make a decision, with higher emotional values or risks attached? For example, a laptop, a smartphone, a vehicle, or a tablet. Please rate the extent to which these statements describe your intention to continue purchasing these types of products with your voice assistant in the future.

We tested these instructions in a pretest. In response to the high-involvement product description, people bought items such as laptops or smartphones, jewelry, or clothes. In response to the low-involvement product description, people reported household items such as toilet paper or soap, books, or groceries. Thus, the instructions seem to work as intended (see supplement).

Desired benefits were assessed with a 10 items scale measuring hedonic, utilitarian, symbolic, and social benefits inspired by McLean and Osei-Frimpong (2019). Respondents rated their agreement on a 7-point Likert scale (1 = *strongly disagree* to 7 = *strongly agree*). Because the original questionnaire assessed *actual* rather than *desired* benefits, we performed a factor analysis supporting the intended four-factor structure (see supplement). Two items assessed hedonic benefits (e.g., "It is important to me to have fun while shopping with my voice assistant", $r = .60$, $N = 423$, $p < .001$), four items utilitarian benefits (e.g., "It is important to me that the voice assistant makes shopping more efficient," C*ronbach's Alpha* = .84), two items symbolic benefits (e.g., "It is important to me that shopping with my voice assistant enhances my image among my peers," $r = .82$, $N = 423$, $p < .001$), and two items measured social benefits (e.g., "I care that shopping with a voice assistant is like dealing with a real person," $r = .77$, $N = 423$, $p < .001$).

User characteristics. We assessed participants' use of smart speaker or tablet, screen use, and voice shopping spendings (see Table in the supplement). We measured *frequency of use* ("How often do you use voice assistant for shopping?") on a single-item 6-point scale from 1 = *almost daily* to 5 = *1–2 times per year* (including an option 6 = *not at all,* ensuring to only survey experienced voice shoppers). *Experience of use* ("Since when do you use voice assistant for shopping purposes?") was measured on a scale ranging from 1 = *5 years or more* to 6 = *less than 12 months*.

Results

Preliminary Analysis

We conducted an ANOVA with repeated measures and post-hoc comparison using Bonferroni correction to test for differences between the dimensions of the relationship perception. Participants saw their relationship with the conversational AI as more strongly characterized by authority ranking (M = 4.85, SD = 1.38, N = 423) than by market pricing (M = 4.42, SD = 1.43, N = 423) and peer bonding (M = 2.61, SD = 1.31, N = 423), all ps < .001, F(1.76, 422.00) = 402.28, p < .001, $\eta^2 part$ = .488 (with Huyn-Feldt correction). For all descriptive results, see Table 4 below.

TABLE 4 Means, Standard Deviations, and Bivariate Correlations (N = 423)

			Human-AI Relationship			Voice Shopping			Desired Benefits		
Scale	*M*	*SD*	PB	AR	MP	GI	LI	HI	HB	UB	SyB
Human-AI Relationship											
Peer Ponding (PB)	2.61	1.31									
Authority Ranking (AR)	4.85	1.38	–.09								
Market Pricing (MP)	4.42	1.43	.47**	.27**							
Voice Shopping											
General Continuance Intention (GI)	5.31	1.3	.20**	.10*	.18**						
Continuance Intention Low-Involvement (LI)	5.40	1.38	.15**	.12**	.14**	.81**					
Continuance Intention High-Involvement (HI)	3.60	1.93	.42**	–.01	.23**	.41**	.38**				
Desired Benefits											
Hedonic Benefits (HB)	4.69	1.21	.34**	.10*	.34**	.30**	.27**	.31**			
Utilitarian Benefits (UB)	5.17	1.09	.20**	.27**	.44**	.42**	.40**	.24**	.51**		
Symbolic Benefits (SyB)	2.30	1.5	.45**	.01	.14**	.14**	.14**	.35**	.35**	.17**	
Social Benefits (SoB)	3.20	1.51	.50**	–.01	.23**	.19**	.19**	.35**	.47**	.33**	.62**

Note. **Bivariate correlation is significant at the .01 level. Correlation is significant at the .05 level.

Main Analyses

General Voice Shopping Intentions (H1 and H2, RQ1)

We tested the predictions that higher values in peer bonding (H1) and market pricing (H2) would predict a stronger general intention to use voice shopping by regressing general voice shopping intentions on the human-AI relationship dimensions. Supporting H1, the regression analysis showed that higher values in peer bonding were associated with a stronger intention to continue voice shopping in general (β = 0.18, p = .001, 95%-CI[0.73,0.29]). H2 was not supported as market pricing did not predict a higher intention to engage in voice shopping (β = 0.07, p = .255, 95%-CI[−0.04,0.16]). The same was true for authority ranking, which was included in the regression for exploratory reasons (β = 0.10, p = .055, 95%-CI[−0.002,0.19]).

Intention to Engage in Low-Involvement Voice Shopping (H3, RQ2)

We hypothesized that the intention to buy low-involvement products is predicted to a stronger extent by peer bonding than by market pricing. Voice shopping intentions for low-involvement products were regressed on the dimensions of human-AI relationship perception. We found that peer bonding predicts intentions to engage in low-involvement shopping (β = 0.15, p = .006, 95%-CI[0.05,0.28]). Market pricing was not associated with low-involvement voice shopping intentions (β = 0.02, p = .684, 95%-CI[−0.09,0.13]). Evidence for H3 was provided by the fact that the CIs for both standardized regression coefficients did not include the respective other regression coefficient. Notably, authority ranking positively predicted intentions to voice shop for low-involvement products (β = 0.15, p = .004, 95%-CI[0.05,0.25]).

Intention to Engage in High-Involvement Voice Shopping (H4, RQ2)

We hypothesized that the intention to buy high-involvement products is predicted to a stronger extent by market pricing than by peer bonding. Voice shopping intentions for high-involvement products were regressed on the dimensions of relationship perception. We found no significant association of market pricing with intentions to engage in voice shopping for high-involvement products (β = 0.04, p = .410, 95%-CI[−0.08,0.20]). However, peer bonding predicted high-involvement shopping intentions (β = 0.40, p < .001, 95%-CI[0.43,0.73]). Thus, we did not find evidence for H4. The intention to buy high-involvement products via voice shopping was not predicted by the market pricing but by the perception of peer bonding relationship (Table 5). The reported correlations did not substantially change when shopping spendings or screen use were included as covariates in the regressions reported so far (for details, see supplement).

TABLE 5 Regression Coefficients of Relational Modes and Shopping Intentions on Desired Benefits (*N* = 423)

Variable	General Voice Shopping	Low-Involvement Voice Shopping	High-Involvement Voice Shopping
	β	β	β
Authority Ranking	.10	**.15***	.02
Market Pricing	.07	.02	.04
Peer Bonding	**.18****	.15*	**.40****

Note. **p* < .05. ***p* < .01. Significant values in bold.

Relation Between Human-AI Relationships, Desired Benefits, and Voice Shopping Intentions (RQ3)

We regressed the relationship dimensions on the desired benefits (see Table 6). Higher values of desired utilitarian benefits were associated with higher values in authority ranking, $\beta = 0.31$, $t(418) = 5.53$, $p < .001$, and market pricing, $\beta = 0.35$, $t(418) = 6.90$, $p < .001$. Market pricing was also predicted by desired hedonic benefits, $\beta = 0.13$, $t(418) = 2.37$, $p = .018$. Higher values in hedonic benefits, $\beta = 0.11$, $t(418) = 2.01$, $p = .037$, desired symbolic, $\beta = 0.22$, $t(418) = 4.17$, $p < .001$, and social benefits, $\beta = 0.31$, $t(418) = 5.37$, $p<.001$, significantly predicted higher values in peer bonding. The other relations were not significant. Then, we regressed the two voice shopping dimensions on the desired benefits, showing that low-involvement shopping was predicted by desired utilitarian benefits ($\beta = 0.35$, $t(418) = 6.65$, $p < .001$). High-involvement shopping, on the other hand, was significantly associated with desired hedonic ($\beta = 0.13$, $t(418) = 2.27$, $p = .024$), symbolic ($\beta = 0.21$, $t(418) = 3.64$, $p < .001$,), and social benefits ($\beta = 0.14$, $t(418) = 2.21$, $p = .028$).

TABLE 6 Regression Coefficients of Relational Modes and Shopping Intentions on Desired Benefits (*N* = 423)

Variable	Authority Ranking	Market Pricing	Peer Bonding	Low-Involvement Voice Shopping	High-Involvement Voice Shopping
Desired Benefits	β	β	β	β	β
Utilitarian Benefits	**.31****	**.35****	.01	**.35****	.10
Hedonic Benefits	–.02	**.13***	**.11***	.06	**.13***
Symbolic Benefits	.04	.00	**.22****	.05	**.21****
Social Benefits	–.12	.06	**.31****	.01	**.14***

Note. **p* < .05. ***p* < .01.

In sum, utilitarian benefits are the primary predictor of authority ranking, market pricing, and low-involvement shopping, whereas hedonic, symbolic, and social benefits are related to peer bonding and high-involvement shopping.

Discussion

The primary goal of this study was to investigate whether voice shopping intentions for low- and high-involvement products depend on how users perceive the human-AI relationships (i.e., peer bonding, market pricing, and authority ranking, based on Tschopp et al., 2023).

Supporting H1, we found that general shopping intentions were predicted by peer bonding, in line with prior research highlighting social dimensions in voice shopping (e.g., Mari & Algesheimer, 2021). Peer bonding showed stronger predictive values for low- and high-involvement shopping than market pricing, supporting H3 but contradicting H4. Peer bonding may not only be relevant for low-involvement shopping but, as indicated by a strong regression coefficient, even more in high-involvement shopping. This is interesting because it contrasts Rhee and Choi's results (2020) with regard to high-involvement shopping yet supports the findings regarding low-involvement shopping. Against our prediction, market pricing was unrelated to shopping intentions (contradicting H2 and H4). Market pricing may not relate to voice shopping, as the rational calculations inherent in market pricing may not be conducive to the presumably swift decision-making process involved in voice shopping. Thus, one could posit that voice shopping appears to be associated more with rapid decision-making than deliberative, slow thinking (cf. Kahneman, 2012). The difference in results compared to Rhee and Choi (2020) could be due to the different study approaches. They conducted an experiment with undergraduates potentially lacking voice shopping experience and confronted them with a shopping scenario—yielding high internal validity, whereas we recruited experienced voice shoppers and asked about their shopping intentions—yielding high external validity.

Our complementary analysis (RQ3) on the desired benefits sheds light on reasons for the strong predictive power of peer bonding. High-involvement shopping (not low-involvement shopping) was related to perceived hedonic, social, and symbolic benefits, which are more socio-emotional in nature. The importance of the socio-emotional dimensions in all facets of voice shopping supports Dellaert et al.'s (2020) claim that AI assistants are more partners in an interactive decision-making process than subservient assistants. Notably, low-involvement shopping was also related to authority ranking (RQ1 and 2), products traditionally associated with utilitarian purposes, where interaction focuses on efficiency.

In sum, people tend to use voice shopping either in a utilitarian manner, by giving orders to their AI assistant, and/or in a more socio-emotional fashion, immersed in a rather emotional shopping experience. No evidence was found for market pricing we assumed to predict high-involvement shopping, invalidating the concept of low- and high-involvement decision-making. Maybe the technology is simply "not there yet," or high-involvement products might be bought via voice shopping after the calculative decision process has been performed.

Implications for Theory

The proposed differentiation of perceived human-AI relationships proved to be helpful to disentangle the consequences of different social perceptions on behavioral intentions. Researchers can use the framework to further explore voice shopping or other functionalities (e.g., smart home) and other applications in the broader AI field (e.g., automated driving). Our study focused on voice shopping intentions, yet if our findings also hold for actual behavior, outcomes have strong practical implications.

Implications for Practice and Policy

System designers may have to rethink effective conversational design strategies tailored to different shoppers as well as shopping scenarios. However, more research is needed to draw safe conclusions. Implications may also arise for business developers choosing the sales channel. For selling low-involvement products, Alexa as a channel might work well despite the lack of control over the conversational design. For high-involvement items, control over the social design might be critical due to the found importance of socio-emotional elements. Thus, with limited control over the social design, Alexa as a sales channel for high-involvement products might not work well. Last but not least, the results may also be relevant for policymakers who further aim to investigate the manipulation and addiction potential of human-AI relationships and the potential facilitation thereof through emotional or personalized social designs (Véliz, 2023). In other words, more evidence is needed on whether these relationship dynamics can be exploited.

Strengths and Limitations

The study enriches the comprehension of the emerging field of voice shopping by investigating experienced voice shoppers and amplifies the value of the perceived human-AI relationships (Tschopp et al., 2023) as predictors thereof. Thereby, this research allows for recommending differentiated voice user interface design strategies and may guide strategic sales channel decisions. A limitation of our findings is the reliance on self-reported shopping intentions instead of actual shopping behavior as well as the lack of cultural variation. Caution is advised regarding the market pricing predictions due to lower scale reliability. The internal consistency was low and could, unfortunately, not be improved by dropping single items. Future research should use longitudinal and/or experimental designs.

Conclusion

We have investigated the influence of differently perceived human-AI relationships on general, high- and low-involvement shopping intentions. The results emphasized the importance of socio-emotional elements (i.e., peer bonding) for voice shopping, in particular for high-involvement products. For low-involvement products, however, the traditional master-servant relationship (i.e., authority ranking) was still found to be relevant. Understanding the impact of multidimensional human-AI relationship perception is relevant for researchers, system designers, and business developers—presumably not only in voice shopping. Additionally, it holds relevance for policymakers, given recent studies pointed out potential negative impacts like user manipulation or addiction through humanized design (Ramadan, 2021).

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