Chatbot or human? The impact of online customer service on consumers' purchase intentions

Article

Accepted Version

Chatbot or human? The impact of online customer service on consumers' purchase intentions

Shili Chen[1], Xiaolin Li[1], Kecheng Liu[2], Xuesong Wang[1]

[1]*Business and Tourism School, Sichuan Agricultural University, Chengdu, China*
[2]*Henley Business School, University of Reading, Whiteknights, United Kingdom*

Abstract
Artificial intelligence (AI) chatbots and human employees have emerged as the dominant forms of online customer service. However, existing research rarely connects the service differences between them in terms of product type, ignoring the interactivity between the two. This study reveals the effect of matching customer service type (AI chatbot vs. human) to product type (search vs. experience) on consumers' purchase intentions through four experiments, revealing the psychological mechanism and boundary condition for the existence of this effect. It shows that (1) the match between customer service type and product type positively affects consumers' purchase intentions; (2) this matching effect is mediated by processing fluency and perceived service quality; and (3) the matching effect works only when consumers' demand certainty is low. These findings enrich the theoretical study of online customer service, and provide marketing insights for companies to improve the adoption of AI chatbots and human employees.

KEYWORDS
online customer service, artificial intelligence, chatbot, human employee, product type, processing fluency, demand certainty

1. INTRODUCTION

With the advent of the digital economy, online shopping has gradually become a mainstream mode of consumption, companies usually provide online customer service to answer their questions. This provides a real-time two-way communication channel for consumers, with a significant impact on consumer satisfaction, repurchases, and word-of-mouth (WOM) intent (Mero, 2018). In the current information age, big data, artificial intelligence, and other technologies are gradually developing, most companies or websites use AI chatbots as customer service assistants for providing consultation services (Longoni et al., 2022; McLeay et al., 2021), such as Taobao's intelligent service — "Alime." With 24/7 real-time services, AI chatbot has significantly improved marketing efficiency (Bock et al., 2020). However, in most cases, consumers prefer human services to intelligent services because of a variety of factors that reflect the "chatbot aversion" phenomenon (Song et al., 2022). For example, interactions between consumers and humans in online interaction contexts last longer than interactions with AI chatbots (Hill et al., 2015).

With the widespread use of AI chatbots, scholarly research on how to efficiently play their role of AI chatbots has increased. As shown in Table 1, majority of articles currently focus on the impact of chatbots on users in terms of communication style, task orientation, and attribute characteristics; fewer articles examine the variability between AI chatbots and human in terms of different tasks. Research suggests that maximizing the advantages of AI chatbots and humans by integrating both into online shopping environments is an important topic of current research (Xiao et al., 2021; Luo et al., 2019); Flavián et al. believe that different characteristics of AI, customer emotions, etc., may have a significant impact on consumers' willingness to interact with AI and use AI services (Flavián et al., 2021).

The most widely used product classification in e-commerce environment is the division between search and experience products (Lee et al., 2014). This study follows the previous division criteria and divides tasks into two types, where users purchase search or experience products. Such products are classified according to whether their critical qualities can be assessed before or after purchase (Franke et al., 2004). The quality of search products can be assessed by objective standard information, and consumers have some knowledge about them before buying. However, the quality of experience products cannot be well assessed until after they are tried or purchased (Klein, 1998; Nelson, 1970).

Previous research has not investigated how different types of online customer service affect consumers' purchase attitudes toward search/experience products. Exploring the service variability between AI chatbots and human employees will help future scholars delve into the effectiveness of AI chatbots. This study seeks to fill this gap by figuring out how the effect of matching customer service type (AI chatbot vs. human) to product type (search vs. experience) on consumers' purchase intentions. Based on the schema congruity theory (Wansink et al., 1996), we expect that people generate different cognitive patterns for AI chatbots and human employees based on their own understanding and prior experience. This eventually leads to positive responses if the pattern of information received by consumers matches the pattern already in the brain; that is, when the pattern of stimulus information matches the pattern stored in the brain (Goodstein, 1993).

This study makes both theoretical and managerial implications to the literature. First, it introduces schema congruity theory (Wansink et al., 1996) to the field of AI chatbot research, extending the scope of this theory to examine the matching effect using empirical data. Next, applying fluency theory (Alter et al., 2009) to the field of online customer service research expands the application of this theory and reveals the psychological mechanisms that impact AI chatbots in e-commerce environments. Finally, based on the uncertainty reduction theory (URT) (Kramer, 1999), consumer demand certainty is introduced into the field of AI chatbot research, highlighting a boundary condition for the matching effect. Practically, this study provides a basis for enterprises to reasonably allocate the dominant tasks of AI chatbots and human employees, which helps optimize the service effectiveness of AI chatbots.

TABLE 1 Partial collation of studies related to AI chatbot and human customer service.

Research	Subjects	Key variables	Findings
Ameen et al., 2022	AI chatbot	chatbot support: assistant vs. friend, body image	Friend-type (vs. assistant-type) chatbots produce positive results on Gen Z women's perceptions of body image and improve buying behavior
Pizzi et al., 2023	AI chatbot	chatbot's direct/averted gaze, perceived warmth/competence	Chatbot with a direct gaze positively influence consumers' willingness to disclose personal information and intentions
Tsai et al., 2021	AI chatbot and human	anger, perceived understanding, interaction satisfaction	When anger is aroused, users are significantly less satisfied with their interactions with chatbots than with human representatives
Rajaobelina et al., 2021	AI chatbot	creepiness, privacy concerns, technology anxiety	Privacy concerns are the biggest factor in creepy interactions with chatbots
Ruan et al., 2022	AI chatbot and human	customer satisfaction, product functional/experiential attributes	Human and AI chatbot customer service have service differentiation in terms of merit and experience products, perceived waiting time, perceived information quality, etc.

Yao et al., 2022	human	social/task-oriented communication style, social distance	Differences in the effects of task-oriented and social-oriented communication styles on willingness to interact
Liu et al., 2023	AI chatbot	humorous emojis, perceived intelligence, implicit personality	Chatbots' use of humorous emojis increases consumers' willingness to reuse them in failure scenarios
Haugeland et al., 2022	AI chatbot	button/free text interaction, topic-led/task-led conversation	Interaction styles and types of conversations in customer service chatbots can affect the user experience
Li et al., 2023	AI chatbot and human	connectivity, association, the frequency of service use	The switching behavior between chatbots and human employees is influenced by the characteristics of both and the situations they face
This research	AI chatbot and human	search/experience products, processing fluency, purchase intention	There is a matching effect between chatbots and human service in terms of experience and search products, and chatbots are better for search products than humans

2. LITERATURE REVIEW AND RESEARCH HYPOTHESES

2.1 The matching effect of customer service type and product type

In e-commerce research, AI is primarily applied to retail service robots (RSR) (e.g., Sophia and Pepper), text-based AI chatbots (e.g., Replika and Alime), and digital voice assistants (e.g., Siri and Alexa) (Shin et al., 2022), all of which have their own definitions and job descriptions, as shown in Table 2. In e-commerce, AI is gradually acting as a human agent for online services, posing a growing threat to human employees (Letheren et al., 2020), especially text-based AI chatbots, and bot services have dramatically changed the e-commerce industry (Wirtz et al., 2018).

TABLE 2 AI bots applied in e-commerce.

AI bot	Definition	Key functions	Relevant studies
retail service robot (RSR) (e.g., Sophia and Pepper)	Automated in-store customer service based on AI technology (Haenlein et al., 2021)	Navigate customers to find products and information, provide personalized advice, place orders online, pick up and deliver to their homes (Mende et al., 2019)	Wang et al., 2022; Borau et al., 2021; Zhang et al., 2023
text-based AI chatbots (e.g., Replika and Alime) (This research)	A new system based on human-computer interaction, natural language processing, and other AI technologies (Sheehan et al., 2020)	24/7 online customer support, storage and tracking of customer data, provide personalized advice and solutions to customer problems (Xu et al., 2020)	Song et al., 2022; Ruan et al., 2022; Sands et al., 2022
digital voice assistants (e.g., Siri and Alexa)	A data program embedded in an IoT device or application (Rabassa et al., 2022)	Communicate and respond to users' voice commands, primarily to identify needs, search for information, make purchases(McLean et al., 2019)	Aw et al., 2022; Lim et al., 2022; Flavián et al., 2023

Consumers' evaluations of products with different attributes lead to different cognitive patterns (Casado et al., 2022). Compared to experience products, search product information is usually standard and objective (e.g., features, performance, etc.), which is difficult to change (Huang et al., 2009); information sources have a weak impact on consumer decisions; and AI chatbots are on an equal footing with humans in terms of information provision (Xie et al., 2022). AI chatbots are considered to have higher agent effectiveness for search products (Gray et al., 2007). From the technical view, bots have high efficiency in coping with targeted, procedural, and repetitive tasks, with a strong ability to identify the information of search products (Castelo et al., 2019). However, when it comes to human service, consumers usually feel that the waiting time is long, which affects their mood (Ruan et al., 2022). Perceived waiting time has a large impact on overall consumer satisfaction (McLean et al., 2017).

For experience products, consumers are more averse to AI performing subjective and highly creative tasks (Castelo et al., 2019). The majority of information about experience products needs to be highly dependent on subjective evaluations; consumers need information after actual experience to remove uncertainty; sources of information have a strong influence on decision-making; human employees are able to provide subjective aspects of information; have intuition, discernment, and a high level of empathy; while AI chatbots are unable to experience or feel (Gray et al., 2007). For information providers, human employees would be the preferred choice for consumers.

Schema congruity theory is divided into two types. The internal brain-based schema can organize the cognitive structures stored in the brain (Wansink et al., 1996); the external stimulus-based schema is used to organize and present individual schemas after the brain receives information from external stimuli. Based on schema congruity theory, we argue that consumers have basic knowledge of different product attributes and AI chatbots; if the obtained information patterns match the product type, consumers will complete a relatively simple and rapid information processing process and generate a more satisfying positive evaluation of that product. In addition, some studies found that interactions with service agents when they meet consumer expectations (Kang, 2006) have a catalytic effect on consumer satisfaction, loyalty, and purchase intentions, ultimately increasing company profits (Reynolds et al., 1999).

In summary, this study proposes the following inferences:

H1a: For search products, AI chatbot service can trigger higher purchase intentions than human

H1b: For experience products, human service can trigger higher purchase intentions than AI chatbot

2.2 The mediating role of processing fluency

Processing fluency refers to the ease with which a consumer identifies or perceives a stimulus target as comprehensible (Alter et al., 2009). Consistency is a determinant of processing fluency. Perceptual coherence may lead to fluency; that is, the higher the content match between cognitive elements, the higher the processing fluency (Winkielman et al., 2012). Consumers have basic knowledge of different product attributes and AI chatbots. As hypothesized previously, based on schema congruity theory, this matching improves processing fluency and allows consumers to produce more favorable target evaluations if the information schema they receive matches the product type (Septianto et al., 2020).

Processing fluency is related to information usability (Hafner et al., 2010), because people assess information fluency based on the information itself. If the processing fluency of information is high, there is an increase in the perceived credibility of the information and its sender (Huang et al., 2018). High fluency suggests that individuals can accurately identify information with less effort, which positively affects the target audience when something is easier to understand, thus increasing attractiveness (Northey et al., 2020). Low fluency states that individuals spend more time and effort on information processing, and are less accurate. People generally perceive less risk in stimuli with high perceived fluency (Balbo et al., 2015); therefore, higher fluency in information processing leads to more positive evaluations and a higher willingness to pay. Online customer service is essentially a source of information for consumers (Ruan et al., 2022), if the information responded to by AI chatbots and human employees can bring high processing fluency to consumers, it will have a positive impact on consumers' evaluation.

We believe that when consumers inquire about product information, the efficient responses of AI chatbots can lead to higher processing fluency compared to human employees, thereby increasing consumers' willingness to purchase. When consumers inquire about product experience information, empathetic human service can lead to higher processing fluency than AI chatbots, increasing consumers' willingness to purchase. Therefore, this study proposes the following hypothesis:

H2: Processing fluency mediates the matching effect between customer service and product types.

2.3 The mediating role of perceived service quality

Service quality is usually a proxy for the overall evaluation of the outcome and process of the service provided by a service provider (Bitner, 1990; Parasuraman et al., 1988). Generally, customers have poor opinions of service quality when they are dissatisfied with a service provider. Therefore, service providers must pay attention to the quality and level of service throughout the service process and improve the level of experience and satisfaction with the service (Rushton et al., 1989).

Unlike processing fluency, consumer perceptions of service quality are based on attitudes perceived during communication with the service provider, such as speed of response and verbal attitude (Kallweit et al., 2014). The impressions of AI service robots on consumers are divided into an overall evaluation and a process evaluation of the tangible service, and service quality of robots has been shown to enhance attitudes and willingness to use service robots (Söderlund, 2022).

Therefore, we propose the following conjecture: when consumers purchase search products, AI chatbot is more capable than humans in bringing them a higher perceived service quality, thus influencing their purchase intention. Similarly, when consumers purchase experience products, humans are more capable than AI chatbots in bringing them a higher perceived service quality, thus influencing their purchase intention.

H3: Perceived service quality mediates the matching effect between customer service and product types.

2.4 The moderating role of consumer demand certainty

Uncertainty reduction theory (URT) argues that uncertainty causes discomfort and anxiety; therefore, individuals are generally motivated by uncertainty reduction (Kramer, 1999). Consumer demand certainty refers to the certainty of information about the chosen good (Urbany et al., 1989), which can be divided into high and low demand certainty states (Kotler, 1967). Consumers with low need certainty have vague purchase goals and difficulty in determining their needs, whereas consumers with high need certainty have relatively clear purchase goals and a clearer perception of their needs (Taylor, 1968). When consumers' need certainty is low, they have a stronger desire for information, and tend to consult sellers about the details of the product to find what they really want; when consumers' certainty is high, they have basic knowledge of the product, and require less details before buying it (Calvo et al., 2001; Taylor, 1968).

When consumer demand certainty is high, consumers' attitudes toward AI chatbots are positively influenced, with the efficiency and accuracy of AI chatbots enhancing consumers' perceived effectiveness (Zhu et al., 2022). Moreover, their attitudes toward human employees are positively changed, with consumers' final decision-making behavior becoming clearer and more focused due to higher demand certainty (Pan et al., 2006). The negative effects of human service, such as perceived waiting time, are reduced as consumers become clearer on their final decisions (Pan et al., 2006). When consumer demand certainty is low, consumers require more information (Calvo et al., 2001) and have no change in attitude toward AI chatbots versus human employees.

Consumers are more receptive to AI chatbots when purchasing search products if demand certainty is high, while there is no effect when purchasing experience products (Zhu et al., 2022). When demand certainty is low, consumers want richer information (Calvo et al., 2001), and they often expect empathy and good communication skills from customer service to deal with their uncertainty (Wien et al., 2021). In summary, this study proposes the conjecture as follows:

H4a: When consumer demand certainty is high, matching customer service type with product type has no effect on consumers' purchase intention.

H4b: When consumer demand certainty is low, matching customer service and product types have an effect on consumers' purchase intentions.

These inferences lead to the research model shown in Figure 1.

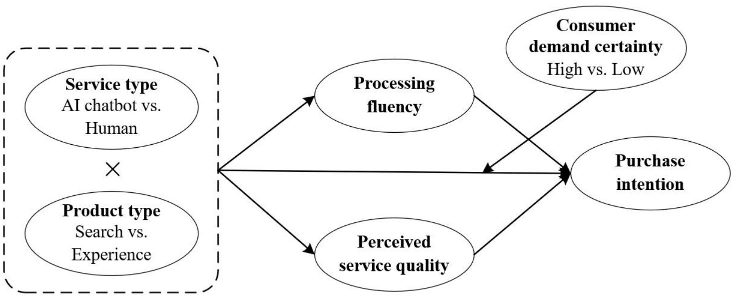

FIGURE 1 Research model.

3. RESEARCH METHODOLOGY

This study examined the effect of matching customer service type (AI chatbot vs. human) to product type (search vs. experience) on consumers' purchase intentions through three dialogue screenshot simulation experiments and one actual interaction experiment, the visual conceptual framework shown in Figure 2.

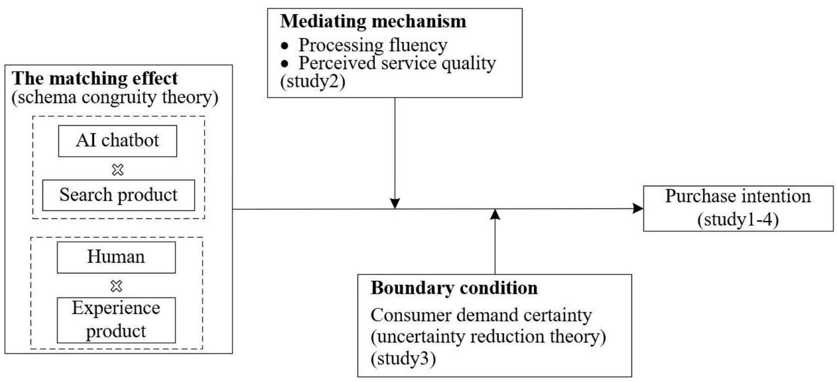

FIGURE 2 Visual conceptual framework.

3.1 Experiment 1: The matching effect of customer service type and product type

Experiment 1 tested the effect of matching customer service with product types on consumers' purchase intentions (tests H1a and H1b). It used a 2 (customer service type: AI chatbot vs. human employee) × 2 (product type: search vs. experience) between-subjects design. As online customer service differs from platform to platform, this study used simulated customer service chat conversations that were text-based and did not contain emoticons or special punctuation. The chat avatars did not contain any attribute features, such as male and female, facial expressions, or other features, to avoid subjects having preferences for specific online customer services that could affect the final experimental results.

3.1.1 Experimental sample information

The recruitment information was published on Credamo, a Chinese data survey platform, and 234 respondents participated in this study. After completing the experiment, they received a certain amount of cash as an experimental reward. Based on the principles of completeness and standardization of completion, 210 valid questionnaires were collected after eliminating invalid questionnaires (AI chatbot and search product, n = 55 vs. human and search product, n = 52; AI chatbot and experience product, n = 52 vs. human and experience product, n = 51). Of the 210 participants, 52.9% were female and 47.1% were male. The percentages of online shopping frequency were 29.5% very often, 22.9% a few times, 20% often, and 1.4% never. Table 3 shows the characteristics of the remaining participants.

TABLE 3 Characteristics of the participants.

	n	%		n	%
Age in years			**Monthly income**		
Below 18	2	1.0	＜￥2000	31	14.8
18 to 25	99	47.1	￥2000 to 5000	82	39.0
26 to 35	97	46.2	￥5001 to 8000	85	40.5
36 or older	12	5.7	＞￥8000	12	5.7
Level of Education			**Occupation**		
Junior college or below	22	10.5	Working	163	77.6
Undergraduate degree	120	57.1	Student	41	19.5
Postgraduate degree or higher	68	32.4	Others	6	2.9

3.1.2 Experimental design and procedures

The experimental material consisted of written material and screenshots of a simulated chat with a store’s online customer service. The manipulation of product types was based on written materials. At the beginning of the experiment, the stimulus materials of the product types were shown to the subjects after describing the definitions of search and experience products in words. Wireless Bluetooth headphones containing both search and experience attributes were selected as the stimulus products. In addition, the headphones belonged to the same type of product for both men and women to avoid gender differences affecting the final results. To exclude the influence of brand awareness, none of the products contained brand information, and their operation was adapted from Huang et al.(2009).

In search product, participants were told that they only required objective criteria information to adequately assess the quality of the headset, such as its Bluetooth model. In experience product, participants were told that in addition to objective criteria information such as the charging time of the headset, they needed to know subjective criteria information that could only be known after use, such as whether the headset was easy to drop while running, and how noisy the headset could be used to answer calls; such information was more valuable. After reading the material, participants were asked to rate the product type on a seven-point Likert scale from 1 = "more similar to experience products" to 7 = "more similar to search products." Participants who passed the product-type stimulus test were then asked if they would like to consult with the store's online customer service, and if so, to continue with the rest of the experiment. The stimulus material for the AI chatbot and human included, in addition to written material, screenshots of a simulated chat with a store's online customer service. Product image and dialogue screenshots can be found in Appendix 1.

To ensure that the participants read the images carefully, the researchers set a minimum reading time of 5 s on the screenshot presentation page. Participants were then asked to rate the type of customer service, using a seven-point Likert scale from 1 = "more similar to human employee" to 7 = "more similar to AI chatbot," to measure the success of the manipulation. After testing this, the participants were asked, "Would you be willing to buy this product, regardless of other factors?" to measure participants' willingness to purchase. In addition, considering that personal usage preferences may have an impact on purchase intention, the question "For search/experience product, do you usually prefer AI chatbots or human for information consultation when shopping online?" was also added. These questions were scored on a 7-point Likert scale. In the last part, participants reported demographic information, such as age and sex.

3.1.3 Experimental results

First, experimental stimuli and operational validity were tested. As shown in Table 4, an independent samples t-test indicates that the subjects perceive a significant difference ($t = -34.747$, $F=12.984$, $p < 0.001$) between the AI chatbot ($M_{machine} = 5.95$, $SD_{machine} = 0.691$) and human employees ($M_{human} = 2.45$, $SD_{human} = 0.763$). In addition, the subjects perceive a significant difference ($t = -34.317$, $F=39.348$, $p < 0.001$) between the search product ($M_{search} = 5.99$, $SD_{search} = 0.558$) and experience product ($M_{experience} = 2.62$, $SD_{experience} = 0.842$).

TABLE 4 Product type and customer service type independent sample t test.

		Levene`s Test for Equality of Variances		t test for Equality of Means				
		F	Sig.	t	df	Sig.(2-tailed)	Mean difference	Std. error difference
product type	Equal variances assumed	39.348	0.000	-34.317	208	<0.001	-3.369	0.098
	Equal variances not assumed			-34.063	176.212	<0.001	-3.369	0.099
customer service type	Equal variances assumed	12.984	0.000	-34.747	208	<0.001	-3.488	0.100
	Equal variances not assumed			-34.680	204.102	<0.001	-3.488	0.101

Second, a matching effect analysis was performed on the data using a two-way ANOVA. Table 5 indicates that the main effect of product type is not significant ($F=1.961$, $p>0.05$), that of customer service type is significant ($F=5.663$, $p<0.001$), and the interaction between customer service and product type is significant ($F=46.912$, $p<0.001$). Since other influencing factors such as sex differences and brand effects were controlled for in this study, only consumers' propensity to use customer service types was used as a control variable. After controlling for the propensity to use customer service type ($F=9.313$, $p<0.05$), the interaction between customer service type and product type remained significant ($F=48.406$, $p<0.001$).

TABLE 5 Between-Subjects effects test of service type and product type.

Source	Type Ⅲ Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	568.575[a]	39	14.579	34.378	<0.001
Intercept	1273.740	1	1273.740	3003.597	<0.001
product type	4.991	6	0.832	1.961	0.074
service type	14.410	6	2.402	5.663	<0.001
product type*service type	537.135	27	19.894	46.912	<0.001
Erro	72.092	170	0.424		
Total	4584.000	210			
Corrected Total	640.667	209			

a. R Squared=0.887(Adjusted R Squared=0.862)

b. Computed using alpha=0.05

The results are shown in Figure 3. In the search product scenario, consumers are more willing to purchase products with the help of AI chatbot than with human ($M_{machine} = 6.06$, $SD_{machine} = 0.844$; $M_{human} = 2.54$, $SD_{human} = 0.803$; $F = 0.658$, $p < 0.001$). Similarly, in the experiential product scenario, consumers are more willing to purchase products with the help of humans than with the AI chatbot customer service ($M_{machine} = 2.94$, $SD_{machine} = 0.639$; $M_{human} = 5.75$, $SD_{human} = 0.614$; $F = 0.003$, $p < 0.001$). The experimental results support H1a and H1b.

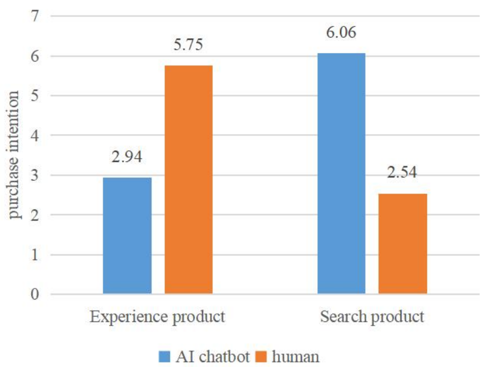

FIGURE 3 The influence of customer service and product type matching on purchase intention.

3.2 Experiment 2: The mediating role of processing fluency and perceived service quality

Experiment 2 examined the mediation mechanism of processing fluency and perceived service quality (tests H2 and H3). The results of Study 1 were tested again with two different types of products to improve the robustness and external validity of the main effects (tests H1a and H1b).

3.2.1 Preliminary experiment

The research objective of the pre-experiment was to select stimulus materials for the products in Experiments 2, 3 and 4. Fifty-eight participants were recruited from the Credamo platform, of whom 55.2% were female and 44.8% were male; 67.2% were 26-35 years old, and 22.4% were 18-25 years old. Based on previous studies, six products were offered in the pre-test, including cell phones, laptops, and cameras, while the experience products included cosmetics, clothes, and shoes (Luan et al., 2016; Nelson, 1970).

The pre-experimental procedure was as follows: First, the subjects were shown the definitions of the two kinds of products. Next, participants rated the six products on a 7-point scale, with 1="more similar to experience product" to 7="more similar to search product." A one-sample t-test of the experimental data showed that cell phones ($M=5.93$, $t=19.713$, $p<0.001$), laptops ($M=6.00$, $t=23.473$, $p<0.001$), and cameras ($M=6.33$, $t=22.694$, $p<0.001$) were judged to be search products, and cosmetics ($M=2.4$, $t=-15.392$, $p < 0.001$), clothes ($M = 2.17$, $t = -16.558$, $p < 0.001$), and shoes ($M = 2.21$, $t = -15.629$, $p < 0.001$) were judged as experience products. Therefore, camera was selected as the search product stimulus material and clothes were selected as the experience product stimulus material for Experiment 2.

3.2.2 Main experiment

Experiment 2 used a 2 × 2 between-subjects design. A total of 240 respondents participated in the study by posting job offers on the Credamo platform, and received a certain amount of cash as payment for the experiment upon completion. Based on the principles of completeness and standardization of completion, 215 completed questionnaires were collected after eliminating invalid questionnaires (AI chatbots and search products, $n = 58$ vs. human and search products, $n = 52$; AI chatbots and experience products, $n = 51$ vs. human and experience products, $n = 54$). Of the 215 participants, 54.9% were female and 45.1% were male; the percentages of online shopping frequency were 48.4% very often, 29.3% a few times, 20.5% often, and 1.4% never. The characteristics of participants can be found in Appendix 5.

The procedure for Experiment 2 was similar to that of Experiment 1, product images and dialogue screenshots can be found in Appendix 2. After reading the experimental material, a measure of processing fluency and perceived service quality was added to the final questions. We used a scale adapted from Graf (2018) to measure the processing fluency variable, with items including "I felt that the customer service response was very easy to understand, the response was very clear, the response was very fluent, and the replies are easy to handle" ($\alpha = 0.964$). Perceived service quality was adapted from Cronin et al. (Cronin Jr et al., 1992; Parasuraman et al., 1988), the items included "customer service responds to problems in a timely manner, customer service handles problems effectively, customer service is polite, and customer service gives personal attention" ($\alpha=0.958$).

3.2.3 Experimental results

Experimental stimuli and operational validity were tested. The independent sample t-tests indicate that the subjects perceived a significant difference between the AI chatbot ($M_{machine} = 6.20$, $SD_{machine} = 0.62$) and human customer service ($M_{human} = 2.25$, $SD_{human} = 0.701$, $t = -43.852$, $F=4.065$, $p < 0.001$). In addition, in the search product scenario, participants preferred to consider the camera as a search product ($M_{search} = 6.17$, $SD_{search} = 0.633$), whereas in experience product, participants were more inclined to consider clothes as an experience product ($M_{experience} = 2.19$, $SD_{experience} = 0.652$), and the product type was manipulated successfully ($t = -45.403$, $F=1.095$, $p < 0.001$). The independent sample t test of product and customer service type can be found in Appendix 8.

The two-way ANOVA showed a significant main effect of product type ($F=3.771$, $p<0.05$) and customer service type ($F=4.013$, $p<0.05$), and a significant interaction between service and product type ($F=72.671$, $p<0.001$). The Between-Subjects effects test of service and product type can be found in Appendix 11. The results are shown in Figure 4. In search product, consumers were more willing to purchase products with the help of AI chatbots than with human customer service ($M_{machine}$ = 6.00, $SD_{machine}$ = 0.749; M_{human} = 2.33, SD_{human} = 0.785; F = 2.489, p < 0.001). Similarly, in experience product, consumers were more willing to purchase products with the help of human customer service than with the AI chatbot ($M_{machine}$ = 2.08, $SD_{machine}$ = 0.523; M_{human} = 5.76, SD_{human} = 0.845; F = 13.772, p < 0.001). The experimental results were tested for H1a and H1b.

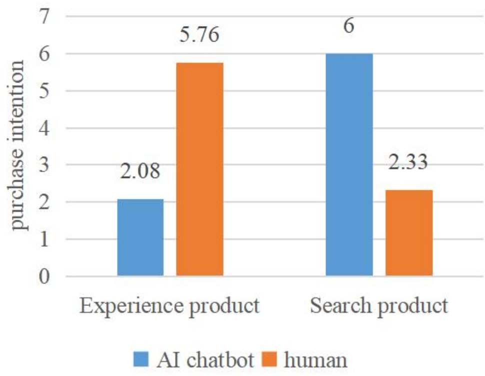

FIGURE 4 The influence of customer service and product type matching on purchase intention.

Bootstrap-mediated effects tests were conducted based on the moderated mediated effects analysis model proposed by Hayes (2017). Model 7 was chosen with a sample size of 5000, and parallel mediation analysis was performed for the two mediating variables at 95% confidence interval. The direct effect value was -0.007; the confidence interval was LLCI=-0.051, ULCI=0.038; the interval contained 0 meaning that the direct effect was not significant. Processing fluency mediated the interaction effect with an effect value of 0.165 and 95 % CI [0.093, 0.244]. Perceived service quality played a mediating role with an effect value of 0.189 and 95 % CI [0.108, 0.269]. Processing fluency and perceived service quality played a fully mediating role.

In addition, using Model 4, we analyzed the mediating effects separately for the search and experience product groups. As shown in Table 6, the mediating effects of processing fluency (b = 0.375, SE = 0.14, 95 % CI [0.089, 0.647]) and perceived service quality (b = 0.38, SE = 0.14, 95 % CI [0.095, 0.648]) were both significant in the search of products. However, the mediating effect of processing fluency (b = -0.229, SE = 0.161, 95 % CI [-0.545, 0.092]) was not significant and perceived service quality (b = -0.437, SE = 0.137, 95 % CI [-0.703, -0.166]) was significant in the experience products.

TABLE 6 The mediating effects of processing fluency and perceived service quality.

effect type			Purchase intention					
			Effect	BootSE	t	p	Boot LLCI	Boot ULCI
direct, mediation and total effect	search product	total effect	0.849	0.037	22.976	0.000	0.776	0.923
		direct effect	0.095	0.108	0.878	0.382	-0.119	0.308
		processing fluency mediation effect	0.375	0.14	—	—	0.089	0.647
		perceived service quality mediation effect	0.380	0.140	—	—	0.095	0.648
	experience product	total effect	-0.883	0.039	-22.741	0.000	-0.960	-0.806
		direct effect	-0.217	0.100	-2.178	0.032	-0.415	-0.019
		processing fluency mediation effect	-0.229	0.161	—	—	-0.545	0.092
		perceived service quality mediation effect	-0.437	0.137	—	—	-0.703	-0.166

3.3 Experiment 3: The moderating role of consumer demand certainty

Experiment 3 focused on whether consumer demand certainty has an effect on the matching effect (tests H4a and H4b), and tested the matching effect, further improving the robustness and external validity of the findings by testing the main effect again with two different types of products.

3.3.1 Experimental design and participants

Experiment 3 used a 2 (customer service type: AI chatbot vs. human employee) × 2 (product type: search vs. experience) × 2 (consumer demand certainty: high vs. low) between-subjects design. A total of 290 valid questionnaires were collected after eliminating invalid questionnaires based on the principles of completeness and normality of completion. Among the 290 participants, 54.5% were female and 45.5% were male; the percentages of online shopping frequencies were 38.6% for very often, 19.7% for several times, 39.7% for often, and 2.1% for never. The characteristics of participants can be found in Appendix 6.

The procedure of Experiment 3 was similar to that of Experiment 1, using the same stimulus method of combining written materials with screenshots. Eight different virtual chat situations were designed, and participants were randomly assigned to any one of them. Based on the pre-experimental results of Experiment 2, a laptop was selected for the search product, and a shoe was selected for the experience product. In addition, compared to Experiment 1, Experiment 3 manipulated the subjects' need certainty, product images and dialogue screenshots can be found in Appendix 3.

After passing the stimulus test for the product type, participants were informed of the level of their demand certainty. In situations with high consumer demand certainty, participants were relatively certain of their purchase needs and clearly knew the model, price, and appearance of the products they wanted. However, in situations with low demand certainty, participants were unclear about the model, price, and appearance of the products they wanted. The participants were asked "Based on the above description, do you think your demand certainty is high or low?" The participants who passed the demand certainty test continued with the rest of the experiment, using a seven-point Likert scale from 1 = "low demand certainty" to 7 = "high demand certainty" to test whether the manipulation was successful. Subsequent experiments were similar to those used in Experiment 1.

3.3.2 Experimental results

Experimental stimuli and operational validity were tested. Independent samples t-tests indicated that subjects perceived AI chatbots ($M_{machine} = 5.99$, $SD_{machine} = 0.807$) to be significantly different from human ($M_{human} = 2.24$, $SD_{human} = 0.762$, $t = -40.692$, $F=0.262$, $p < 0.001$); in the search product scenario, subjects were more inclined to view laptops as search products ($M_{search} = 6.13$, $SD_{search} = 0.592$). In the experience product scenario, subjects were more inclined to view shoes as experience products ($M_{experience} = 2.03$, $SD_{experience} = 0.802$, $t = -49.414$, $F=19.827$, $p < 0.001$). In addition, participants were more inclined to perceive their demand certainty as high in scenarios where demand certainty was high ($M_{high} = 6.02$, $SD_{high} = 0.823$), and low in scenarios where demand certainty was low ($M_{low} = 2.02$, $SD_{low} = 0.699$, $t = -44.612$, $F=4.610$, $p < 0.001$). The independent sample t test of product and customer service type can be found in

Appendix 9.

Analysis of the moderating effect of demand certainty. The data were analyzed using a three-way ANOVA, which showed significant main effects for product type (F=4.837, p<0.001), service type (F=3.172, p<0.05), demand certainty (F=46.407, p<0.001), and their interactions (F=4.165, p< 0.001). The Between-Subjects effects test of service and product type can be found in Appendix 12. The results are shown in Figures 5 and 6, where the interaction effect is significant in the context of low demand certainty (F=42.201, p<0.001). Specifically, in search products, consumers were more likely to purchase products with the help of AI chatbots than humans ($M_{machine}$ = 5.83, $SD_{machine}$ = 0.923; M_{human} = 2.37, SD_{human} = 0.808; F = 0.316, p < 0.001). In experience products, consumers were more likely to purchase products with the help of humans than AI chatbots ($M_{machine}$ = 1.71, $SD_{machine}$ = 0.732; M_{human} = 5.97, SD_{human} = 0.788; F = 0.046, p < 0.001), thus confirming Hypothesis 4b

By contrast, the interaction effect between service and product types was not significant in the scenario of high demand certainty (F=1.127, p>0.1). Specifically, For experience products, there was no significant difference between customer service types ($M_{machine}$ = 5.95, $SD_{machine}$ = 0.78; M_{human} = 5.76, SD_{human} = 0.819; F = 0.153, p > 0.1). For search products, consumers were more willing to purchase products with the help of AI chatbots than human services ($M_{machine}$ = 5.97, $SD_{machine}$ = 1.04; M_{human} = 5.19, SD_{human} = 1.327; F = 2.55, p < 0.05), partially verifying Hypothesis 4a.

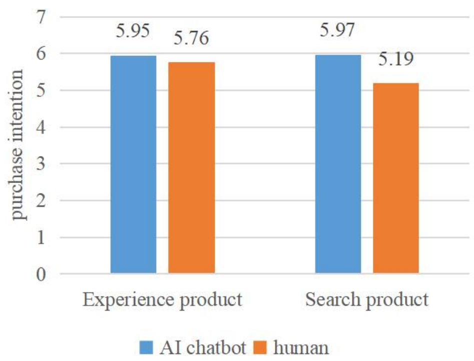

FIGURE 5 The effect of high demand certainty group.

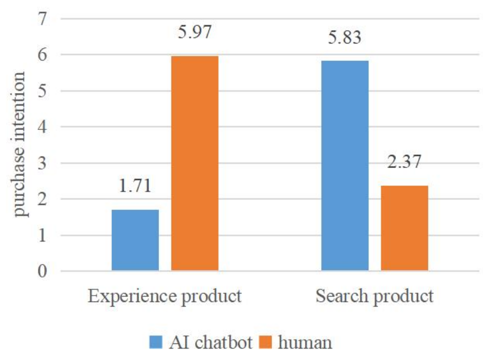

FIGURE 6 The effect of low demand certainty group.

3.4 Experiment 4: Testing main effect in a realistic interaction setting

Experiment 4 was conducted in an actual interaction setting, and the purpose of the study was to examine the main effects, transform purchase intention into actual purchase behavior, and explore the effects of matching different customer service types with product types on consumers' willingness to pay. It was highlighted that researchers can start with laboratory experiments to first support the theoretical evidence presented in the study, thereby checking external validity through actual interactions that can further improving the robustness and external validity of the findings (Viglia et al., 2021).

3.4.1 Experimental design and participants

Experiment 4 used a 2 (customer service type: AI chatbot vs. human) × 2 (product type: search vs. experience) between-subjects design. Job postings were made on the Credamo platform, and 220 respondents participated in the study, receiving a certain amount of cash as experimental compensation upon completion of the experiment. Based on the principle of completeness and standardization of completion, 203 completed questionnaires were collected after eliminating invalid questionnaires (AI chatbot and search product, n = 51; human and search product, n = 51; AI chatbot and experience product, n = 51; human and experience product, n = 50). Of the 203 participants, 45.3% were female and 54.7% were male; the percentages of online shopping frequency were 32.5% very often, 35% a few times, and 32.5% often. The characteristics of participants can be found in Appendix 7.

The process of Experiment 4 was similar to that of Experiment 2, and the product settings and selection were the same as those in Experiment 2. Experiment 4 did not use screenshots, but used WeChat applets (app) to create an actual shopping environment, allowing subjects to click on the link to enter the product interface, view the product interface, click on [Customer Service] at the bottom left of the page, enter the customer service real-time dialogue chat box, and communicate with the AI chatbot or human. During the real-time communication, the subjects were required to communicate 2-3 product questions with customer service. After the above steps, the participants were asked to return to the product interface and choose whether to click [Buy Now] to generate an order for the purchase (without paying; the order result was visible in the app background). Product Interface and dialogue screenshots can be found in Appendix 4. In addition, participants were asked, "To what extent would you engage in payment behavior, regardless of other factors?" to measure the participants' willingness to pay.

3.4.2 Experimental results

Experimental stimuli and operational validity were tested. The independent samples t-test indicated that subjects perceived a significant difference ($t = -34.304$, $F=0.715$, $p < 0.001$) between the AI chatbot ($M_{machine} = 5.97$, $SD_{machine} = 0.826$) and human ($M_{human} = 1.93$, $SD_{human} = 0.852$). For search product, subjects preferred to consider the camera as a search product ($M_{search} = 5.96$, $SD_{search} = 0.832$); for experience product, subjects were more inclined to consider clothes as an experience product ($M_{experience} = 2.03$, $SD_{experience} = 0.842$); and product type was manipulated successfully ($t = -33.463$, $F=0.184$, $p < 0.001$). The independent sample t test of product and customer service type can be found in Appendix 10.

Customer service type and purchasing decisions (measured by whether an order was generated) were used as dichotomous variables for the chi-square tests. The search product group data revealed the following: AI chatbot × purchase, n=47; chatbot × no purchase, n=4; human × purchase, n=8; and human × no purchase, n=43. A chi-square test between the customer service type group and purchasing decisions group as categorical variables showed a significant difference between the two groups ($\chi^2=74.655$, $p<0.001$). While data from the experience product group showed AI chatbot × purchase, n=6; AI chatbot × no purchase, n=45; human × purchase, n=46; and human × no purchase, n=4. A chi-square test using the customer service type and purchasing decisions groups as categorical variables showed a significant difference between the two groups ($\chi^2=79.767$, $p<0.001$).

A two-way ANOVA was conducted with willingness to pay as the dependent variable. The main effect of product type was not significant ($F=1.934$, $p=0.078$), the main effect of customer service type was not significant ($F=0.485$, $p=0.787$), and the interaction between customer service and product type was significant ($F=20.791$, $p<0.001$). The Between-Subjects effects test of service and product type can be found in Appendix 13. Results are shown in Figure 7, where consumers were more willing to pay with the help of AI chatbots than humans for search product ($M_{machine} = 5.78$, $SD_{machine} = 0.879$; $M_{human} = 2.53$, $SD_{human} = 1.027$; $F = 2.695$, $p < 0.001$). Similarly, in experience product, consumers were more willing to pay with the help of humans than with AI chatbot customer service ($M_{machine} = 2.16$, $SD_{machine} = 1.102$; $M_{human} = 5.5$, $SD_{human} = 0.995$; $F = 0.019$, $p < 0.001$).

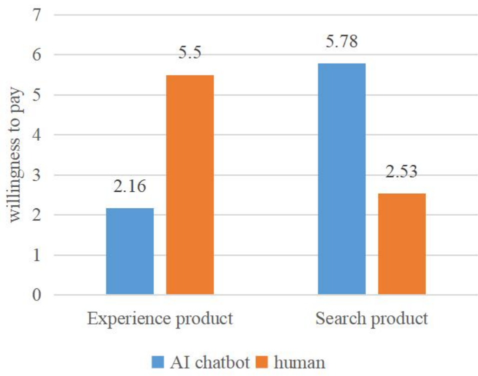

FIGURE 7 The influence of customer service and product type matching on willingness to pay.

3.5 Overall discussion of the experiment

As shown in Table 7, the hypothetical conjectures presented in this study were tested through three dialogue screenshot simulation experiments and one actual interaction experiment. In addition, Experiment 4 explored the matching effect on actual purchase behavior, and further explored the effect on willingness to pay.

TABLE 7 Summary of experiments.

Experiment	Experimental method	Experimental design	Hypothesis testing
Experiment 1	dialogue screenshot simulation experiment	2 (AI chatbot vs. human) × 2 (search vs. experience) between-subjects design	H1a, H1b established
Experiment 2	dialogue screenshot simulation experiment	2 (AI chatbot vs. human) × 2 (search vs. experience) between-subjects design	H1a, H1b, H2, H3 established
Experiment 3	dialogue screenshot simulation experiment	2 (AI chatbot vs. human) × 2 (search vs. experience) × 2 (consumer demand certainty: high vs. low) between-subjects design	H4a, H4b established
Experiment 4	practical interaction experiment	2 (AI chatbot vs. human) × 2 (search vs. experience) between-subjects design	H1a, H1b established

4. RESEARCH FINDINGS AND DISCUSSION

4.1 Research conclusions

This study examined the impact of matching customer service type (AI chatbot vs. human) with product type (search vs. experience) on consumers' purchase intentions in terms of both psychological mechanisms and boundary conditions. Through four experiments, the following conclusions were obtained: (1) When purchasing search products, AI chatbot can trigger higher purchase intention than human; when purchasing experience products, human can trigger higher purchase intention than AI chatbot (Experiment 1).

(2) The psychological mechanism underlying the matching effect between customer service and product types includes two paths: processing fluency and perceived service quality. When customer service and product types have a matching effect, processing fluency and perceived service quality play a complete mediating role. In the experience product group, the influence of processing fluency diminishes, consumers

pay more attention to each other’s service quality, and the company needs to focus on enhancing service quality (Experiment 2).

(3) The certainty of consumer demand influences the matching effect. When consumer demand certainty is low, the matching effect still works; when consumer demand certainty is high, this effect does not work. However, for search products, AI chatbots work better than humans, regardless of high or low demand certainty (Experiment 3). (4) Through actual interaction experiments, we found that the matching effect exists in terms of actual purchase behavior, with no change in the effect on willingness to pay, further validating the dual effect of matching on consumer psychology and behavior (Experiment 4).

4.2 Theoretical contributions

This study focuses on the matching effect of customer service and product type on purchase intentions in an e-commerce context. First, previous related research has mostly focused on the characteristics of AI robot service and the willingness to use it (Chi et al., 2022), which does not explore the difference between AI chatbots and humans (Luo et al., 2019).

In addition, this study responds to the call for research on whether users prefer to use AI chatbots or humans, and how to assign the dominant tasks of the two types of service agents based on task features (Robinson et al., 2020). It provides both psychological and actual behavioral evidence to provide a new perspective for studying the impact of AI chatbots on consumers. This study applies schema congruity theory to the matching of product and customer service types. Previous studies have mainly explored product material (Gao et al., 2022), product reviews (Filieri et al., 2021), and product-color (Ketron et al., 2020) temperature consistency, but not addressed the study of schema consistency between product and customer service, extending the application of the theory.

Second, this study reveals the psychological mechanism of processing fluency (Alter et al., 2009). Previous researches have concentrated on the role of processing fluency in terms of emojis (Wu et al., 2022), the number of images (Invernizzi et al., 2022), and labels (Mauri et al., 2021). This study not only extends the application of fluency theory in e-commerce research, but also provides a theoretical basis for better understanding the cognitive state of consumers. Additionally, revealing that differences in service effectiveness occur between different customer service types when faced with different products. Finally, based on the uncertainty reduction theory (URT) (Kramer, 1999), this study clarifies the boundary conditions under which the matching effect occurs, that is, the consumers’ demand certainty. Therefore, this study extends the theory to AI chatbots, and enriches the scope of the theory.

4.3 Managerial implications

This study provides references and guidance for lead task allocation and management optimization of AI chatbots and human employees in online shopping. First, the finding that matching product type to customer service type significantly affects consumers’ purchase intentions suggests that companies need to specify the types of product attributes that customers inquire about before arranging for an appropriate online customer service agent. Moreover, the finding that processing fluency and perceived service quality play a mediating role in the matching effect suggests that consumers’ desire to purchase is triggered only when they perceive higher fluency and service quality. Companies can optimize the application of chatbots based on consumer needs, and build a good digital and intelligent structure to better meet these needs.

This study further reveals the boundary conditions under which the matching effect occurs. The matching effect works only when consumer demand certainty is low; the matching effect fails when consumer demand certainty is high. However, for search products, the services of AI chatbots can trigger higher purchase intentions from consumers than human employees. Therefore, enterprises can identify consumers' demand certainty by interacting with customers and analyzing their previous data, thus providing the most appropriate type of service.

4.4 Limitations and future research

This study has some limitations and offers potential research directions for future studies. First, according to previous studies on service bot applications, the different attribute types of chatbots (capable vs. enthusiastic, anthropomorphic vs. mechanical) and interaction modes (high vs. low engagement) may affect consumers' acceptance (Zhang et al, 2023; Belanche et al., 2020), and the attributes of AI have a significant impact on consumer acceptance, satisfaction, etc. (Flavián et al., 2021). Therefore, future research could use chatbots with different attribute characteristics as independent variables to explore whether a matching effect exists between chatbots with search and experience product tasks.

Second, based on the suggestion that augmented reality needs to be planned for deployment throughout the online purchase process, this technology provides consumers with three-dimensional virtual objects, and superimposes them onto the real environment (Hilken et al., 2022). The use of AI chatbots and augmented reality interactive technology (ARIT) enhances consumer satisfaction and influences revisits to online stores and shopping intentions (Moriuchi et al., 2021; Ameen et al., 2022). Future research could explore the differences between augmented reality and AI chatbot technologies in the provision of information services, and whether they play different roles across product types.

In addition, this study explored text-based chatbots, and voice-based chatbots (e.g., Siri and Alexa) have been used in the online customer service industry as intelligent assistants (Aw et al., 2022; Akdim et al., 2023). Future research could use voice-based chatbots as research subjects to explore the differences between them and humans. Finally, the boundary condition of this study is based on the general perception of consumers that AI chatbots are less capable of handling uncertainty. The influence of consumers' demand certainty on their acceptance of AI chatbots may change as AI chatbots are developed and improved (Zhu et al., 2022). Future studies also could include variables that may impact the interaction, such as perceived waiting time and perceived interaction quality, to deepen the investigation of the intrinsic mechanisms in the process of producing a matching effect.

REFERENCES

Akdim, K., & Casaló, L. V. (2023). Perceived value of AI-based recommendations service: the case of voice assistants. Service Business, 17(1), 81-112.

Alter, A. L., & Oppenheimer, D. M. (2009). Uniting the tribes of fluency to form a metacognitive nation. Personality and social psychology review, 13(3), 219-235.

Ameen, N., Cheah, J. H., & Kumar, S. (2022). It's all part of the customer journey: The impact of augmented reality, chatbots, and social media on the body image and self-esteem of Generation Z female consumers. Psychology & Marketing, 39(11), 2110-2129.

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

Balbo, L., & Jeannot, F. (2015). The fit between message framing and temporal distance: An efficient way to promote an innovative product. Recherche et Applications en Marketing, 30(1), 28-49.

Belanche, D., Casaló, L.V., Flavián, C., & Schepers, J. (2020). Service robot implementation: A theoretical framework and research agenda. The Service Industries Journal, 40 (3–4): 203-225.

Bitner, M.J. (1990). Evaluating service encounters: the effects of physical surroundings and employee responses. Journal of Marketing, 54(2): 69-82.

Bock, D. E., Wolter, J. S., & Ferrell, O. C. (2020). Artificial intelligence: Disrupting what we know about services. Journal of Services Marketing, 34(3), 317–334.

Borau, S., Otterbring, T., Laporte, S., & Fosso Wamba, S. (2021). The most human bot: Female gendering increases humanness perceptions of bots and acceptance of AI. Psychology & Marketing, 38(7), 1052-1068.

Calvo, M.G., & Castillo, M.D. (2001). Selective interpretation in anxiety: Uncertainty for threatening events. Cognition & Emotion, 15 (3): 299-320.

Casado, L., Sánchez-Fernández, J., & Viedma-del-Jesús, M. (2022). Neural responses to hedonic and utilitarian banner ads: An fMRI study. Journal of Interactive Marketing, 57(2), 296–322.

Castelo, N., Bos, M.W., & Lehmann, D.R. (2019). Task-dependent algorithm aversion. Journal of Marketing Research, 56(5): 809-825.

Chi, O.H., Gursoy, D., & Chi, C.G. (2022). Tourists' attitudes toward the use of artificially intelligent (AI) devices in tourism service delivery: Moderating role of service value seeking. Journal of Travel Research, 61 (1): 170-185.

Cronin Jr, J.J., & Taylor, S.A. (1992). Measuring service quality: a reexamination and extension. Journal of Marketing. 56(3): 55-68.

Filieri, R., Javornik, A., Hang, H., & Niceta, A. (2021). Environmentally framed eWOM messages of different valence: The role of environmental concerns, moral norms, and product environmental impact. Psychology & Marketing, 38(3), 431-454.

Flavián, C., Akdim, K., & Casaló, L. V. (2023). Effects of voice assistant recommendations on consumer behavior. Psychology & Marketing, 40(2), 328-346.

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

Franke, G.R., Huhmann, B.A., & Mothersbaugh, D.L. (2004). Information content and consumer readership of print ads: A comparison of search and experience products. Journal of the Academy of Marketing Science, 32(1): 20-31.

Gao, X., De Hooge, I. E., & Fischer, A. R. (2022). Something underneath? Using a within-subjects design to examine schema congruity theory at an individual level. Journal of retailing and consumer services, 68, 102994.

Goodstein R C. (1993). Category-based applications and extensions in advertising: Motivating more extensive ad processing. Journal of consumer research, 20(1), 87-99.

Graf, L. K., & Mayer, S. (2018). Landwehr, J. R. Measuring processing fluency: One versus five items. Journal of Consumer Psychology. 28(3), 393-411.

Gray, H. M., Gray, K., & Wegner, D. M. (2007). Dimensions of mind perception. science, 315(5812), 619-619.

Haenlein, & Kaplan, A. (2021). Artificial intelligence and robotics: Shaking up the business world and society at large. Journal of Business Research, 124, 405-407.

Hafner, M., & Stapel, D. (2010). Information to go: Fluency enhances the usability of primed information. Journal of Experimental Social Psychology, 46 (1), 73-84.

Haugeland, I. K. F., Følstad, A., Taylor, C., & Bjørkli, C. A. (2022). Understanding the user experience of customer service chatbots: An experimental study of chatbot interaction design. International Journal of Human-Computer Studies, 161, 102788.

Hayes, A. F. (2017). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. Guilford publications.

Hilken, T., Keeling, D. I., Chylinski, M., de Ruyter, K., Golf Papez, M., Heller, J., ... & Alimamy, S. (2022). Disrupting marketing realities: A research agenda for investigating the psychological mechanisms of next-generation experiences with reality-enhancing technologies. Psychology & Marketing, 39(8), 1660-1671.

Hill, J., Ford, W.R., & Farreras, I.G. (2015). Real conversations with artificial intelligence: A comparison between human-human online conversations and human-chatbot conversations. Computers in Human Behavior, 49, 245-250.

Huang, P., Lurie, N.H., & Mitra, S. (2009). Searching for experience on the web: An empirical examination of consumer behavior for search and experience goods. Journal of Marketing, 73(2): 55-69.

Huang, Y., Li, C., Wu, J., & Lin, Z. (2018). Online customer reviews and consumer evaluation: The role of review font. Information & Management, 55(4): 430-440.

Invernizzi, A. C., Bellucci, M., Acuti, D., & Manetti, G. (2022). Form and substance: Visual content in CSR reports and investors' perceptions. Psychology & Marketing, 39(5), 974-989.

Kallweit, K., Spreer, P., & Toporowski, W. (2014). Why do customers use self-service information technologies in retail? The mediating effect of perceived service quality. Journal of Retailing and Consumer Services, 21(3): 268-276.

Kang, G. D. (2006). The hierarchical structure of service quality: integration of technical and functional quality. Managing Service Quality: An International Journal, 16 (1), 37-50.

Ketron, S., & Spears, N. (2020). Schema-ing with color and temperature: The effects of color-temperature congruity and the role of non-temperature associations. Journal of Retailing and Consumer Services, 54, 102021.

Klein, L. R. (1998). Evaluating the potential of interactive media through a new lens: Search versus experience goods. Journal of Business Research, 41(3), 195-203.

Kotler, P. (1967). Managerial marketing, planning, analysis, and control. Englewood iffes, NJ: Prentice Hall.

Kramer, M. W. (1999). Motivation to reduce uncertainty: A reconceptualization of uncertainty reduction theory. Management Communication Quarterly, 13(2), 305-316.

Lee, E. J., & Shin, S. Y. (2014). When do consumers buy online product reviews? Effects of review quality, product type, and reviewer's photo. Computers in Human Behavior, 31(4), 356–366.

Letheren, K., Russell-Bennett, R., & Whittaker, L. (2020). Black, white or grey magic? Our future with artificial intelligence. Journal of Marketing Management, 36(3-4): 216-232.

Li, C. Y., & Zhang, J. T. (2023). Chatbots or me? Consumers' switching between human agents and conversational agents. Journal of Retailing and Consumer Services, 72, 103264.

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

Liu, D., Lv, Y., & Huang, W. (2023). How do consumers react to chatbots' humorous emojis in service failures. Technology in Society, 73, 102244.

Longoni, C., & Cian, L. (2022). Artificial intelligence in utilitarian vs. hedonic contexts: The "word-of-machine" effect. Journal of Marketing, 86(1): 91-108.

Luan, J., Yao, Z., Zhao, F., & Liu, H. (2016). Search product and experience product online reviews: An eye-tracking study on consumers' review search behavior. Computers in Human Behavior, 65: 420-430.

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. Marketing Science, 38(6): 937-947.

Mauri, C., Grazzini, L., Ulqinaku, A., & Poletti, E. (2021). The effect of front-of-package nutrition labels on the choice of low sugar products. Psychology & marketing, 38(8), 1323-1339.

McLean, G., & Osei-Frimpong K. (2017). Examining satisfaction with the experience during a live chat service encounter-implications for website providers. Computers in Human Behavior, 76, 494-508.

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

McLeay, F., Osburg, V.S., Yoganathan, V., & Patterson, A. (2021). Replaced by a Robot: Service Implications in the Age of the Machine. Journal of Service Research, 24(1): 104-121.

Mende, M.L., Scott, J., & van Doorn, D. (2019). Grewal, I. Shanks. Service robots rising: How humanoid robots influence service experiences and elicit compensatory consumer responses. Journal of Marketing Research, 56 (4), 535-556.

Mero, J. (2018). The effects of two-way communication and chat service usage on consumer attitudes in the e-commerce retailing sector. Electronic Markets, 28, 205-217.

Moriuchi, E., Landers, V. M., Colton, D., & Hair, N. (2021). Engagement with chatbots versus augmented reality interactive technology in e-commerce. Journal of Strategic Marketing, 29(5), 375-389.

Nelson, P. (1970). Information and consumer behavior. Journal of political economy, 78(2): 311-329.

Northey, G., Dolan, R., Etheridge, J., Septianto, F., & Esch, P.V. (2020). LGBTQ Imagery in Advertising: How Viewers' Political Ideology Shapes Their Emotional Response to Gender And Sexuality in Advertisements. Journal of Advertising Research, 60 (2): 222-236.

Pan, B., & Fesenmaier, D. R. (2006). Online information search: Vacation planning process. Annals of Tourism Research, 33 (3), 809-832.

Parasuraman, A., Zeithaml, V., & Berry, L.L. (1988). SERVQUAL: a multiple-item scale for measuring customer perceptions of service quality. Journal of Retailing, 64: 420-450.

Pizzi, G., Vannucci, V., Mazzoli, V., & Donvito, R. (2023). I, chatbot! the impact of anthropomorphism and gaze direction on willingness to disclose personal information and behavioral intentions. Psychology & Marketing.

Rabassa, V., Sabri, O., & Spaletta, C. (2022). Conversational commerce: Do biased choices offered by voice assistants' technology constrain its appropriation?. Technological Forecasting and Social Change, 174, 121292.

Rajaobelina, L., Prom Tep, S., Arcand, M., & Ricard, L. (2021). Creepiness: Its antecedents and impact on loyalty when interacting with a chatbot. Psychology & Marketing, 38(12), 2339-2356.

Reynolds, K. E., & Beatty, S. E. (1999). Customer benefits and company consequences of customer-salesperson relationships in retailing. Journal of Retailing, 75(1), 11-32.

Robinson, S., Orsingher, C., Alkire, L., De Keyser, A., Giebelhausen, M., Papamichail, K.N., & Temerak, M.S. (2020). Frontline encounters of the AI kind: An evolved service encounter framework. Journal of Business Research, 116, 366-376.

Ruan, Y., & Mezei, J. (2022). When do AI chatbots lead to higher customer satisfaction than human frontline employees in online shopping assistance? Considering product attribute type. Journal of Retailing and Consumer Services, 68, 103059.

Rushton, A. M., & Carson, D. J. (1989). The marketing of services: managing the intangibles. European Journal of Marketing, 23(8), 23-43.

Sands, S., Campbell, C., Plangger, K., & Pitt, L. (2022). Buffer bots: The role of virtual service agents in mitigating negative effects when service fails. Psychology & Marketing, 39(11), 2039-2054.

Septianto, F., Northey, G., Chiew, T.M., & Ngo, L.V. (2020). Hubristic pride & prejudice: The effects of hubristic pride on negative word-of-mouth. International Journal of Research in Marketing, 37 (3): 621-643.

Sheehan, B., Jin, H.S., & Gottlieb, U. (2020). Customer service chatbots: Anthropomorphism and adoption. Journal of Business Research, 115, 14-24.

Shin, H., Bunosso, I., & Levine, L. R. (2022). The influence of chatbot humour on consumer evaluations of services. International Journal of Consumer Studies, 47(2), 545–562.

Söderlund, M. (2022). Service robots with (perceived) theory of mind: An examination of humans' reactions. Journal of Retailing and Consumer Services, 67, 102999.

Song, M., Du, J., Xing, X., & Mou, J. (2022). Should the chatbot "save itself" or "be helped by others"? The influence of service recovery types on consumer perceptions of recovery satisfaction. Electronic Commerce Research and Applications, 55, 101199.

Taylor, R. S. (1968). Question-Negotiation and Information Seeking in Libraries. College & Research Libraries, 29 (3), 178-194.

Tsai, W. H. S., Lun, D., Carcioppolo, N., & Chuan, C. H. (2021). Human versus chatbot: Understanding the role of emotion in health marketing communication for vaccines. Psychology & marketing, 38(12), 2377-2392.

Urbany, J.E., Dickson, P.R., & Wilkie, W.L. (1989). Buyer uncertainty and information search. Journal of Consumer Research, 16 (2): 208-215.

Viglia, G., Zaefarian, G., & Ulqinaku, A. (2021). How to design good experiments in marketing: Types, examples, and methods. Industrial marketing management, 98, 193-206.

Wang, Y., Kang, Q., Zhou, S., Dong, Y., & Liu, J. (2022). The impact of service robots in retail: Exploring the effect of novelty priming on consumer behavior. Journal of Retailing and Consumer Services, 68, 103002.

Wansink, B., & Ray, M. L. (1996). Advertising strategies to increase usage frequency. Journal of Marketing, 60(1), 31-46.

Wien, A.H., & Peluso, A.M. (2021). Influence of human versus AI recommenders: The role of product type and cognitive processes. Journal of Business Research, 137: 13-27.

Winkielman, P., Huber, D. E., Kavanagh, L., & Schwarz, N. (2012). Fluency of consistency: When thoughts fit nicely and flow smoothly. Cognitive consistency: A fundamental principle in social cognition, 89-111.

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: service robots in the frontline. Journal of Service Management, 29(5), 907-931.

Wu, R., Chen, J., Wang, C. L., & Zhou, L. (2022). The influence of emoji meaning multipleness on perceived online review helpfulness: The mediating role of processing fluency. Journal of Business Research, 141, 299-307.

Xiao, L., & Kumar, V. (2021). Robotics for customer service: a useful complement or an ultimate substitute? Journal of Service Research, 24(1): 9-29.

Xie, Z., Yu, Y., Zhang, J., & Chen, M. (2022). The searching artificial intelligence: Consumers show less aversion to algorithm-recommended search product. Psychology & Marketing, 39(10), 1902-1919.

Xu, Y., Shieh, C. H., van Esch, P., & Ling, I. L. (2020). AI customer service: Task complexity, problem-solving ability, and usage intention. Australasian Marketing Journal, 28(4), 189-199.

Yao, Q., Kuai, L., & Wang, C. L. (2022). How frontline employees' communication styles affect consumers' willingness to interact: The boundary condition of emotional ability similarity. Journal of Retailing and Consumer Services, 68, 103082.

Zhang, A., & Rau, P.L.P. (2023). Tools or peers? Impacts of anthropomorphism level and social role on emotional attachment and disclosure tendency towards intelligent agents. Computers in Human Behavior, 107415.

Zhu, Y., Zhang, J., Wu, J., & Liu, Y. (2022). AI is better when I'm sure: The influence of certainty of needs on consumers' acceptance of AI chatbots. Journal of Business Research, 150: 642-65.