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When do AI chatbots lead to higher customer satisfaction than human frontline employees in online shopping assistance? Considering product attribute type

Yanya Ruan [a], József Mezei [b,*]

[a] School of Management, Guangzhou University, No.230, Outer Ring West Road, Higher Education Mega Center, Guangzhou, 510006, China
[b] Faculty of Social Sciences, Business and Economics, Åbo Akademi University, Vänrikinkatu 3 B, 20500, Turku, Finland

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ABSTRACT

The increasing adoption of AI chatbots in online shopping assistance, as a complement or substitute for human frontline employees (HFLEs), leads to the question whether HFLEs perform better than AI service robots and why. From the perspective of product attribute type (experiential/functional) and focusing on customer satisfaction, this study explores how the impact of service agent on customer satisfaction varies along with product attribute type. A scenario-based experiment was designed and completed by 567 participants. Although HFLEs lead to higher customer satisfaction when the product attribute is experiential, AI chatbots perform better than HFLEs when the product attribute is functional. We make use of perceived information quality, perceived waiting time, and positive emotions, three determinants of customer satisfaction, to explain the variation of the role of different service agent types. The findings offer useful implications for companies when selecting service agent types in online shopping assistance.

1. Introduction

Serving as a bridge between the company and customers, human frontline employees (HFLEs) are inseparable from customer service, playing a key role in fulfilling customer value delivery (Malhotra et al., 2013; Steinhoff and Zondag, 2021). Through information provision, responding to customer requests, as well as product recommendation, HFLEs realize customer shopping assistance service. Existing research links the performance of HFLEs to customer service quality, customer satisfaction and transaction success (Farrell et al., 2001; Holmqvist et al., 2019; Matthews et al., 2020). However, recent advances in service artificial intelligence (AI) show a diminishing role of HFLEs in customer service, particularly in customer shopping service. AI chatbots are increasingly utilized in frontline interactions, as a complement or even substitute for HFLEs, to provide shopping service (Luo et al., 2019). Especially in online marketplaces, although interactions between customers and HFLEs remain commonplace, AI chatbots have undertaken a considerable part of online shopping service tasks. As announced by Deloitte in the 'Double11' shopping festival of 2018, over 98 percent of customer assistance in T-mall (www.Tmall.com) was conducted by AI chatbots, which greatly relieves the workload of HFLEs (Deloitte). Due to their superior efficiency, AI chatbots are deployed widely in online shopping assistance, and the acceptance and performance of AI chatbots have attracted increasing research interest (Li et al., 2020a; Adam et al., 2021; Luo et al., 2019; Pantano and Pizzi, 2020).

The role of AI chatbots in customer satisfaction, a core dimension of customer service performance, has been emphasized (Ashfaq et al., 2020; Eren, 2021; Crolic et al., 2022). However, at the current stage the combination of HFLEs and AI chatbots is still the dominant form of service agents in online shopping service (Luo et al., 2019). Some studies suggest that it is necessary to distinguish the roles of HFLEs and AI chatbots in online frontline interactions and determine how, when, and to what extent to integrate AI chatbots into online shopping service strategies (Xiao and Kumar, 2021; Robinson et al., 2020; Bock et al., 2020). Following this perspective, researchers found that AI contributes significantly to customer service performance through assisting HFLEs as service-related software (Henkel et al., 2020). In addition, when considered as service agents interacting with customers directly, AI chatbots and HFLEs are both found to be associated with customer satisfaction (Prentice et al., 2020; Xiao and Kumar, 2021). However, AI chatbots are powerless to gain customer preference compared to HFLEs (Prentice et al., 2020; Luo et al., 2019). More importantly, the impact of

* Corresponding author.
E-mail addresses: ruanyy@gzhu.edu.cn (Y. Ruan), jmezei@abo.fi (J. Mezei).

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AI service quality on customer satisfaction even becomes negative and insignificant when AI chatbots work in combination with HFLEs (Prentice and Nguyen, 2020). These findings seem inconsistent with the statement of Wirtz et al. (2018), in that AI chatbots and HFLEs should dominate different types of service tasks by virtue of their distinct features and service capabilities. Furthermore, the potential effect of diverse service circumstances proposed by some researchers seems to have drawn limited consideration in these studies (Luo et al., 2019; Xiao and Kumar, 2021).

Focusing on this inconsistent effect, other researchers propose that the role of AI and HFLEs in affecting customer satisfaction and its antecedent, service quality, may vary across service circumstances. Specifically, AI chatbots and other AI service robots perform better than HFLEs in some situations (i.e., B2C firms, utilitarian service categories, and low-equity brands), while HFLEs dominate in some other situations (i.e., B2B firms, hedonic service categories, and high-equity brands) (Xiao and Kumar, 2021). Similarly, in traditional service contexts, customer satisfaction generated by HFLEs' service is also found to vary along with different service circumstances such as utilitarian/hedonic service context and core/relational service delivery (Jiang and Wang, 2006; Rod et al., 2016). One reason underlying this phenomenon is that the influence of cognitive evaluation and positive emotions, two primary elements affecting customer satisfaction, vary across service circumstances (Jiang and Wang, 2006; Moliner-Velázquez et al., 2019).

However, among the factors (i.e., service characteristics, brand equity and the nature of firm) proposed to moderate the comparative superiority of HFLEs and AI chatbots in online shopping service satisfaction Xiao and Kumar (2021), product attributes, which are classified into functional attributes and experiential attributes (Brakus et al., 2014; Kong et al., 2020), have not been discussed adequately. According to prior literature, product attribute type influences customers' cognitive processes and/or affective response to the product or service (Baltas et al., 2017; Brakus et al., 2014; Estes et al., 2018), leading to a difference in customer shopping behavior or customer satisfaction (Lee and Hosanagar, 2021; Wang et al., 2018). Considering the proposal that it is necessary to rethink the role of service agents in customer satisfaction in the AI service era (Bock et al., 2020; Pelau et al., 2021), the role of product attribute types needs to be studied when attempting to explore the differences between HFLEs and AI chatbots in customer satisfaction in the context of online shopping assistance. Following this view, this study attempts to answer the following research question:

RQ *How does product attribute type (functional vs. experiential) impact customer satisfaction in customer's interaction with online assistance (human vs. AI)?*

2. Theoretical background and hypotheses development

In this article, motivated by the challenges and opportunities discussed in the previous section, we will focus on a situation in which AI-based chatbots play an increasingly important role: online shopping assistance. In a typical scenario, the service agent, being a human or AI-based, interacts with the customer through a chat window in the form of text messages; in this study we will focus on the agent's task of providing information about a product. Based on the literature, as we will present in this section, we created a model as depicted in Fig. 1. We identified Perceived Information Quality, Perceived Waiting Time, Pleasure and Arousal as variables having an impact on customer satisfaction in the described scenario; moreover, we hypothesize these relationships to be moderated by the product attribute type focused on in the interaction between the customer and the (AI or human) frontline employee. In the following, we will motivate and present the hypotheses emerging from the research model.

2.1. Service agent types, product attribute types and customer satisfaction

Customer satisfaction is a result of customer expectation confirmation (Christ-Brendemühl and Schaarschmidt, 2020; Ashfaq et al., 2020; Eren, 2021). Customer expectation, according to previous literature, can be strongly associated with customer purchase motivations. The customers who are motivated by utilitarian/functional goals, expect to make an informed choice that meets their functional goals, while the customers driven by hedonic or experiential goals desire to gain favorable feelings (i.e., pleasure and excitement) or avoid negative feelings from the purchasing or consumption experience (Barbopoulos and Johansson, 2016; Arnold and Reynolds, 2012).

Corresponding to these goals, product attributes in general consist of tangible and intangible features of a product, such as benefits, functions, uses, as well as sensory and affective attributes (Keller and McGill, 1994; Lee et al., 2011; Brakus et al., 2014). Referring to their distinct roles in consumer consumption, existing research segments product attributes into functional attributes (utilitarian attributes) and experiential attributes (non-functional or hedonic attributes) (Brakus et al., 2014; Kong et al., 2020). Functional attributes refer to the ones capable of serving as

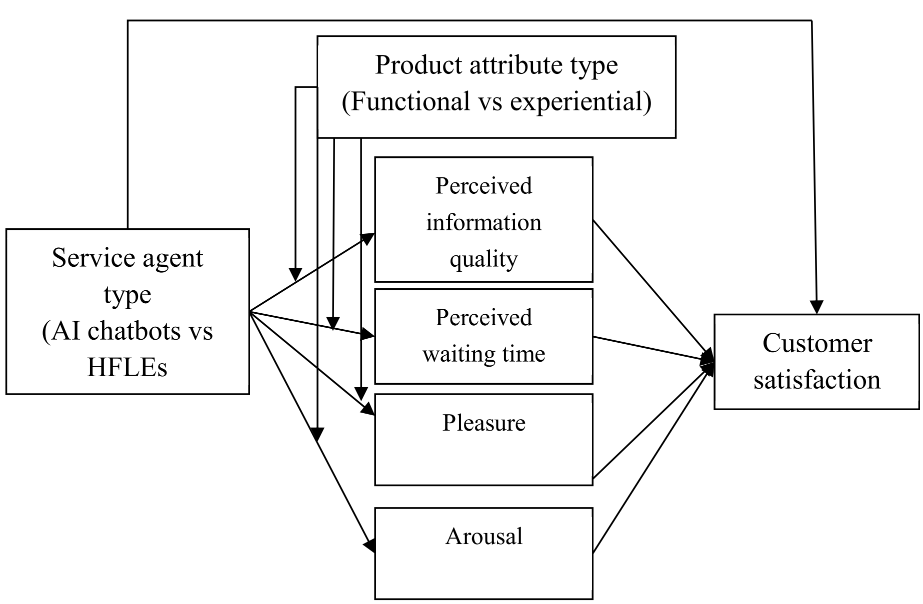


Fig. 1. Research model.

instruments towards fulfilling some consumer objectives. This is typically a tangible material objective relevant to some fundamental human need, such as the materials of clothing and the performance of a mobile phone (Lehdonvirta, 2009). In contrast, experiential attributes are associated with consumers' aesthetic pleasure and entertaining experiences (Brakus et al., 2009; Chattaraman et al., 2010), referring to the attributes powerful to affect consumer sensory perception, moods, emotions and feelings, such as product color, shapes, design and taste (Brakus et al., 2014). Accordingly, people will be primarily motived by utilitarian/functional goals when seeking information for product functional attributes but primarily driven by hedonic/experiential goals when intending to know more about product experiential attributes.

In traditional transaction contexts, product attribute type is found critical to customer satisfaction (Slevitch and Oh, 2010; Wang et al., 2018; Peng et al., 2019). In addition, the impact of environmental stimuli (i.e., online retailer's deceptive practices, store image and aesthetics) on customer satisfaction is moderated by product type characterized by different product attribute types (Román, 2010; Moliner-Velázquez et al., 2019). Compared to purchasing a functional product, purchasing an experiential/hedonic product seems to make customers weight environmental stimuli more favorable, thereby leading to a more significant relationship between environmental stimuli and customer satisfaction. However, the question whether there is a similar influence mechanism underlying the effect of product attribute type in the context where HFLEs and chatbots work together has not been discussed adequately. Only a handful of studies propose that customer satisfaction influenced by different service agents (AI vs. human) would vary across product/service categories (hedonic/experiential vs utilitarian/functional) (Xiao and Kumar, 2021).

According to the limited existing literature, AI chatbots are suggested not to be very competent in providing hedonic services because of their limits in creating emotive and affective experience. In contrast, they are found to be superior in the utility-based service scenarios where the efficient and functional aspects are emphasized (Xiao and Kumar, 2021). Especially when hedonic outcomes are weighed less, AI chatbots are more welcomed as an instrument for communication (Li et al., 2021). Thereby, we hypothesize that:

H1a. *AI chatbots perform better regarding customer satisfaction when communication is initiated for product functional attributes*

H1b. *HFLEs perform better regarding customer satisfaction when the communication is focused on product experiential attributes*

2.2. Cognitive-affective model of customer satisfaction

The cognitive-affective model of customer satisfaction, one of dual-process models, has been widely utilized in the research on customer satisfaction (Coursaris and Van Osch, 2016; Marques et al., 2021). The model states that customers should not be considered as cognitive beings only, as customer satisfaction is influenced by both customer cognitive judgements and emotion. Specifically, on one hand, customer satisfaction is affected by a customer's cognitive evaluation on the performance of a product or service based on his/her prior expectation; on the other hand, customer satisfaction originates from the customer' s affective response to the product/service-related or environment-related stimuli (Caro and García, 2007). In this model, affect contributes directly to customer satisfaction and partially mediates the impact of cognitive evaluation on customer satisfaction (Liljander and Strandvik, 1997; Caro and García, 2007; Keiningham et al., 2017; Oliver, 1993; Song and Qu, 2017). In this research, we consider perceived information quality and perceived waiting time of the cognitive dimension, and positive emotions (pleasure and arousal) of the affective dimension.

In fact, customers' cognitive judgement and affect are not independent variables, and are influenced by many extrinsic factors, such as staff/salespeople characteristics, customer service and shopping environment (Wong and Wan, 2013; Hunneman et al., 2017; Demoulin and Willems, 2019). Customers' cognitive judgement, on one hand, is the result of customers' deliberate reasoning process about functional value during shopping, not only regarding the product evaluation, but also the assessment of staff/salespeople service (i.e., interaction quality and information quality) (Brakus et al., 2014; Ertekin et al., 2020). On the other hand, cognitive judgement is influenced by salespeople characteristics (i.e., employee apparel) which are considered as simple service quality cues (Yan et al., 2011; Barney et al., 2020). With regard to customer affect, prior literature reveals that good staff/salespeople service performance and favorable shopping/consumption environment are beneficial to customers' positive affect (i.e., pleasure and arousal) (Ryu et al., 2021; Lin, 2016). Some other frontline interaction-related stimuli, such as employee-displayed smiling and employees' communication accommodation strategies, are also found to positively influence customer affect (Otterbring, 2017; Wang et al., 2015). Thereby, we propose that in online assistance service, customers' cognitive responses (i.e., perceived information quality and perceived waiting time) and affective response (i.e., positive emotions) will be influenced by service agent types (AI chatbots vs HFLEs).

2.2.1. Relationship between service agent types, product attribute types and perceived information quality

Conveying product information to customers clearly is one of the most important components of frontline salespeople service, both in the context of business-to-business and business-to-consumer (B2C) (Ahearne et al., 2007; Kalra et al., 2021; Hughes et al., 2019). Even in e-commerce, where product information becomes more readily available to customers and online reviews serve as another information source for customers, the information from FLEs is still important to decision-making, especially in case of high customer involvement (Hochstein et al., 2019). The quality of information resulting from the communication between FLEs and customers not only influence transaction success (Hochstein et al., 2021), but are also considered as determinant of customer satisfaction or customer relationship (Fergurson et al., 2021; Zhang et al., 2020).

Perceived information quality implies an information receiver's perception of the information quality. Information quality, in line with the research of Lee et al. (2002), can be segmented into four sub-classes, with intrinsic information quality and contextual information quality being the most widely utilized. Intrinsic information quality implies that information has quality on its own right, and this can be reflected in the completeness, accuracy, validity and believability of the information concerning the products/service offered (Wang and Strong, 1996; Lee et al., 2002). Contextual information quality highlights the consideration of information within the context of the task at hand, emphasizing the value-added, relevant, timeliness and appropriate amount of the information (Lee et al., 2002; Ponte et al., 2015; Wang and Strong, 1996). Although many studies do not distinguish between these two sub-classes clearly when discussing the role of information quality on customer attitude and behaviors, the dimensions of these two sub-classes are widely adopted in the studies simultaneously (Xu et al., 2020; Geebren et al., 2021). Following these studies, the intrinsic and contextual aspect of information quality are both considered in this research.

Perceived information quality during customer decision-making, is viewed as the individual's object-based beliefs, powerful to shape satisfaction towards the information providers or shopping experience (Wixom and Todd, 2005; Ghasemaghaei and Hassanein, 2015; Kim and Lim, 2001). In fact, not only in traditional service contexts, but also in the new context of AI customer service, information quality is found associated with customer satisfaction towards AI service as well (Ashfaq et al., 2020; Prentice et al., 2020). Thereby, the perceived quality of information provided by service agents, including AI chatbots and HFLEs, will positively influence customer satisfaction.

In the context of online shopping assistance, AI chatbots and HFLEs work in combination to provide product information and suggestions. As the result of their different features, HFLEs, especially the experienced ones, typically perform better in providing customized and personalized information or suggestions based on their deep understanding of customers and service processes. In contrast, AI chatbots are likely to be more effective at providing complete, current and detailed objective product information based on mechanical or analytical system learning (Wirtz et al., 2018; Wien and Peluso, 2021). As we know from the literature, the customers driven by utilitarian/functional goals pay more attention to the objective quality and performance of products and make more comparison among alternatives based on the information of product functions and performance (Li et al., 2020a). This information can also be provided effectively, even more completely, neutrally, and objectively by AI chatbots (Li et al., 2020a), and consequently AI chatbots would be perceived as effective information providers as HFLEs at the least, and the functional attribute information provided by AI chatbots would be considered as higher quality.

Conversely, when customers assess product experiential attributes, especially experiential product/service, subjective information (i.e., others' reviews, opinions, or suggestions) is likely to be more useful (Bae and Lee, 2011; Wien and Peluso, 2021). A main reason for this is that product experiential elements are associated with individuals' sensations, feelings, emotions and imaginations, and their performance cannot be defined only by objective product information but also require descriptions based on personal feelings and experience (Couwenberg et al., 2017; Wilcox et al., 2011). In this context, although AI chatbots can mimic emotions and provide information like HFLEs based on system learning (Wirtz et al., 2018), customers still feel that AI chatbots are incapable to experience the product genuinely. Thereby, the superiority of HFLEs to describe product experiential attributes based on factual information and genuine emotional perceptions and experience will make HFLEs more expert in providing experiential information than AI chatbots. Hence, we hypothesize that,

H2a. *In online shopping assistance, the quality of information about product functional attributes provided by AI chatbots is perceived superior to the information provided by HFLEs.*

H2b. *In online shopping assistance, the quality of information about product experiential attributes provided by HFLEs is perceived superior to the information provided by AI chatbots.*

2.2.2. Relationship between service agent types, product attribute types and perceived waiting time

Waiting is an inseparable component of customers' experience of shopping or acquiring a service, occurring both in offline and online scenarios (Lee et al., 2012). Perceived waiting time refers to a user/customer's perception of the amount of time he/she waits for before his/her request is responded to (Antonides et al., 2002). Beyond objective waiting time, which is considered as the basic component of people's perception of waiting time (Weijters et al., 2007), some research has confirmed that perceived waiting time is influenced by customers' tolerance of waiting as well (Baker and Cameron, 1996; Pruyn and Smidts, 1998). Many stimuli, such as the (monetary) costs of waiting, the service environment and the characteristics of filler interfaces in online environments, are identified as factors influencing customers' tolerance of waiting (Antonides et al., 2002; Baker and Cameron, 1996; Lee et al., 2012; Djelassi et al., 2018).

Under human-computer interaction or online employee-customer interaction, shortening waiting time or perceived waiting time can lessen a user's/customer's dissatisfaction of waiting, and increases his/her overall satisfaction significantly (Djelassi et al., 2018; McLean and Osei-Frimpong, 2017). As for the information provider (i.e., information system or HFLEs), its response time towards information requirement is also important to user/customer satisfaction (Chi, 2018; McLean and Osei-Frimpong, 2017; Zhang et al., 2020). Therefore, under online shopping assistance, a customer's perception of waiting time associated with service agents' response to his/her requirement will affect his/her satisfaction.

However, customers' tolerance of waiting varies along with purchase motives (hedonic or utilitarian). Although customers normally have higher desire to seek the convenience of saving time and the ease of accessing information through different online channels for utilitarian purchases (vs hedonic purchase), they are likely to spend more time to understand the hedonic product when making a hedonic purchase (Anderson et al., 2014; Li et al., 2020b). In other words, customers' tolerance of waiting is higher during hedonic purchases than during utilitarian purchases. On one hand, this weakens the advantages of AI chatbots in shortening perceived waiting time in the scenario of hedonic purchases, and on the other hand, makes the disadvantages of HFLEs related to timely responds to hedonic purchase assistance less important. Even more, when the efficiency of HFLEs increases with the experience they gain, HFLEs would perform better than AI chatbots. Thereby, we hypothesize that,

H3a. *In online shopping assistance, AI chatbots perform better than HFLEs in shortening perceived waiting time when responding to customers' consultation about product functional attributes.*

H3b. *In online shopping assistance, HFLEs perform better than AI chatbots in shortening perceived waiting time when responding to customers' consultation about product experiential attributes.*

2.2.3. Relationship between service agent types, product attribute types and positive emotions

Emotion, viewed as a specific example of affect, refers to 'a mental state of readiness that arises from cognitive appraisal of event or thoughts, has a phenomenological tone, is accompanied by physiological processes, is often expressed physically and may result in specific actions to affirm or cope with the emotion, depending on its nature and the person having it' (Bagozzi et al., 1999). Compared to moods, another example of affect occurring in the absence of conscious awareness of stimulus event, emotions are more stimuli specific (Spielman et al., 1988). Furthermore, they are valenced affective reactions to situations, being segmented into positive and negative ones (Clore et al., 1987). In the context of marketing or consumer consumption, pleasure and arousal are typically utilized as two vital dimensions to mirror consumer emotions (Richins, 1997; Das and Varshneya, 2017).

Pleasure and arousal, the positive emotions evoked by favorable marketing stimuli or customers' appraisal of events, according to previous literature, are of benefit to customer satisfaction (Otterbring, 2017; Kastenholz et al., 2018; Chatterjee et al., 2021; Tueanrat et al., 2021). Serving as two factors reflecting customers' feeling of happiness or excitement, respectively, they are related significantly to frontline service, not only in service consumption situations, but also in the context of product purchasing (Jiang and Wang, 2006; Vigolo et al., 2020; Schill and Godefroit-Winkel, 2021). Consumers' affective state varies across the performance of frontline service, including experiential service and utilitarian service (Vigolo et al., 2020), and in the context of experiential/hedonic consumption situations, it is even statistically more important than cognition to explain customer satisfaction (Krampf et al., 2003; Bigné et al., 2008). Since service encounter between customers and service agents is ubiquitous in online shopping assistance, for an experiential or utilitarian goal, there will be an impact of positive emotions (pleasure and arousal) on customer satisfaction.

Customer emotions during purchasing or consumption can be triggered by a set of stimuli, among which frontline service encounter is considered as a vital one (Babin et al., 1995; Schill and Godefroit-Winkel, 2021; Maguire and Geiger, 2015). HFLEs' affective delivery during employee-customer interaction is found to be important to understand customer emotions. In line with emotional contagion theories, one's expression of positive or negative emotions can elicit corresponding emotional state in others (Hatfield and Cacioppo, 1994). HFLEs' affective delivery through greeting, speaking in a rhythmic vocal tone, smiling, making eye contact, thanking, and talking actively is of benefit to invoke positive customer emotions (Lin and Lin, 2011, 2017; Otterbring, 2017). Even in the context of e-service encounters, the impact of HFLEs' affective delivery on customer emotions is established (Turel et al., 2013; Ma and Wang, 2021). E-smile or other emoticons evoke customer affective responses significantly.

The setting is similar in online shopping assistance where different service agents interact with customers for service offering. Through instant messaging software, various emoticons and particular cyber-speak (i.e., Qin) are widely utilized to express FLEs' emotions (Li et al., 2019; Ma and Wang, 2021). This emotional experience sharing between employees and customers will influence customer emotions (Zablah et al., 2017). Regarding AI chatbots, although AI training enables them to simulate human's emotional expressions, utilizing similar emoticons and cyber-speak to influence customer emotions, customer affective responses to service agents' positive emotion display are not simply dependent on the form of employee affective delivery, influenced by the authenticity of service agents' positive emotion display. While authentic positive emotion display contributes to positive customer affective responses, the inauthentic positive emotion display does not (Turel et al., 2013; Lechner and Paul, 2019). Therefore, AI chatbots without authentic emotions would have limitations in evoking positive emotions, and HFLEs will perform better during employee-customer interaction.

However, beyond as it is elicited by employee-customer interaction, customers' emotions are also affected by service quality. High-quality service is normally found to be positively and significantly associated with customer positive emotions (Le et al., 2020; Schill and Godefroit-Winkel, 2021). Apart from traditional dimensions of service (i.e., reliability, responsiveness, assurance, and empathy), service convenience, customized service and the relevance of information offered during purchase process are confirmed to be the determinants of customers' positive emotions (Ladhari et al., 2017; Kim, 2021). Since AI chatbots can provide objective information without delay while HFLEs are capable of offering customized service (Wirtz et al., 2018), when focusing on the effect of customer service on customers' emotions, AI chatbots would perform better under the scenario associated with product functional attributes while HFLEs would be superior under the scenario related to product experiential attributes.

Regarding the effects of employee-customer interaction and the process touch point on customers' emotions, existing research finds that they are moderated by customer purchase goals (hedonic vs utilitarian goals) (Stein and Ramaseshan, 2019). Specifically, the effect of process touch point on customers' affective responses is significantly stronger for utilitarian goals than for hedonic goals, while employee-customer interaction contributes more significantly to customers' affective responses for hedonic goals than for utilitarian goals. Thereby, we hypothesize that,

H4a. *In online shopping assistance, AI chatbots lead to higher pleasure than HFLEs in customers' consultation about product functional attributes.*

H4b. *In online shopping assistance, HFLEs lead to higher pleasure than AI chatbots in customers' consultation about product experiential attributes.*

H5a. *In online shopping assistance, AI chatbots lead to higher arousal than HFLEs in customers' consultation about product functional attributes.*

H5b. *In online shopping assistance, HFLEs lead to higher arousal than AI chatbots in customers' consultation about product experiential attributes.*

Finally, the presented discussion about the interaction of product attribute types and determinants of the cognitive-affective model results in a further hypothesis about the nature of the relationship between the components as depicted in Fig. 1:

H6. *The interaction effect of service agent type by product attribute type toward service satisfaction is mediated by (a) perceived information quality, (b) perceived waiting time, (c) pleasure and (d) arousal.*

3. Methodology

To test these proposed hypotheses, a between-subjects scenario-based experiment was conducted. Scenario-based experimental approach has been used to investigate the effect of stimuli on people's attitude or reactions in frontline service interactions (Boukis et al., 2020; McLeay et al., 2021; Hochstein et al., 2021), as identified as appropriate for this study.

3.1. Research design

The setting of this experiment was a simulative online shopping assistance communication occurring in T-mall, a leading B2C platform where most retailers provide online shopping assistance through chatbots and HFLEs simultaneously. A 2(Service agent type: AI chatbots vs. HFLEs) × 2(Product attribute type: functional and experiential) between-subjects experiment was designed to test proposed hypotheses. Four scenarios were created and every scenario contained a pre-experiment task and an experiment task. The respondents arranged into one of the scenarios randomly were invited to conduct the pre-experiment task first. A brief description of a product was displayed and the respondents were informed to focus on a particular utilitarian/experiential attribute of the product. After reading the product description, the respondents who thought that it was necessary to interact with online service agent to get more information about the attribute were permitted to conduct the main experiment task. Every scenario included two products, but only one product was presented to each respondent randomly.

3.2. Materials

Before creating online shopping assistance communication, products used in the study were selected. In order to eliminate the potential bias caused by the product type when assessing the effect of product attribute type (Lehmann and O'shaughnessy, 1974; Baltas et al., 2017), a utilitarian product (air fryer), a hedonic product (perfume), a product containing functional and experiential attributes (coat) were chosen. This setting is similar to the strategy followed by Sela and Berger (2012), who use three different products randomly assigned to the participants in order to assess the importance of attribute types and quantity (completely hedonic, completely utilitarian, or a mix of hedonic and utilitarian attributes). The attribute(s) and attribute values for each product are given in Table 1.

The communications between the service agent and the customer were created based on the product attributes mentioned above. They were created based on the corresponding original conversations obtained in T-mall. In order to obtain original conversations, we initiated different dialogues with service agents in three online stores (the stores selling air fryers, perfume and coats, respectively). In the dialogues about an air fryer, questions about the cooking function of the air fryer were asked. In the dialogues about perfume, questions about its ascent were asked. In the dialogues about a coat, its insulating power (functional) and its visual effect (experiential) were discussed. These conversations were adopted into corresponding communications that were

Table 1
Product attribute(s) and attribute values used in the experiment.

Products	Functional attributes	Experiential attribute
Air fryer	Cooking function	–
Perfume	–	Scent
Coat	Insulating power	Visual effect

used in the scenarios .[1] In order to exclude the potential effect of conversation length on perceived waiting time, the number of customer questions among different product attributes were manipulated to be similar. However, considering the difference in responding time between AI chatbots and HFLEs, the responses of AI chatbots were shown immediately but the presentation of HFLEs' response had a 2-s delay (but not between HFLEs' response and the consumer's next question), which was less the maximum tolerable delay in the context of responses time (Gunarathne et al., 2018; Luo et al., 2019). Participants were reminded that the service agent was writing before the responses presented just like that in real online chatting situations under the scenarios of HFLEs service. Considering the ubiquitous mobile commerce, all scenarios were designed for a mobile-commerce interface. Participants were invited to conduct the experiment via mobile phones.

3.3. Measures

Perceived information quality: it is measured using perceived intrinsic information quality and perceived contextual information quality. 10 items, adapted from Lee et al. (2002) and Setia et al. (2013), were used to measure the three dimensions of perceived intrinsic information quality: 4 items for completeness, 3 items for accuracy and 3 items for believability. In addition, another 10 items, adapted from Lee et al. (2002), were utilized to measure the three dimensions of perceived contextual information quality: 4 items for relevance, 3 items for timeliness and 3 items for appropriate amount. All items were measured using a 7-point Likert scale, ranging from "1-strongly disagree" to "7-strongly agree". The items are presented in Appendix A.

Perceived waiting time: A 3 item-scale adapted from McLean and Osei-Frimpong (2017) was used to measure perceived waiting time (see Appendix A). All items were measured using a 7-point Likert scale, ranging from "1-strongly disagree" to "7-strongly agree". Corresponding to the items, a high value indicates that the waiting time is appropriate/acceptable/as expected, while a low value indicates longer than expected waiting times.

Pleasure: Pleasure was measured using a 3 item-scale adapted from Hsieh et al. (2021). Items such as 'unhappy to happy' were measured using a 7-point Likert scale, ranging from "1-unhappy/annoyed/despairing" to "7-happy/pleased/hopeful".

Arousal: Two items adapted from Hsieh et al. (2021) were used to measure arousal. The items were measured using a 7-point Linkert scale as well, ranging from "1-relaxed/calm" to "7-stimulated/excited" (see Appendix A).

Customer satisfaction: measured using a 3 item-scale adapted from Nunkoo et al. (2020). The scale consisted of items that were measured by a 7-point Likert scale (ranging from "1-strongly disagree" to "7-strongly agree") (see Appendix A).

Covariates: in order to exclude the potential effect of socio-demographic characteristics on customers' responses, gender, age, educational background, and monthly expense were controlled in this study.

3.4. Procedure and participants

The experiment was conducted online on December 22nd, 2021. Participants were recruited through http://www.wjx.cn, a popular online survey platform with more than 2.6 million active users in China. Using the paid service provided by the platform, a link titled 'A simple scenario-based experiment about frontline interaction experience in T-mall' was distributed randomly to the users http://www.wjx.cn. All respondents were arranged randomly to one of the four scenarios and were invited to conduct the pre-experiment task first. In this task, the respondents were asked to imagine the situation where they intended to purchase a product (an air fryer, perfume (as a gift for a good friend) or a coat) online and were browsing the description of an option. The choice of specifying perfume as a gift is two-fold (as done similarly by Wang et al. (2017) and Palcu et al. (2017)). First, customers' preference for the scent of a perfume is very personalized (Hämmerli et al., 2012), and thus a description not in line with the preferences can cause negative bias, which is not the case when perfume is purchased for somebody else as a gift. Second, perfume is often considered as a product for females who represent a majority of customers (Salem, 2018), and conversely, many males buy perfume as a gift (Branco-Illodo et al., 2020). Indeed, perfume is a typical product in gift market (Wang and Van Der Lans, 2018).

The description of the product was displayed to the respondents. After browsing, the respondents who thought that it was not necessary to consult the service agent further about specific attributes of the product were excluded, using the criterion of "whether you will consult the service agent to know more about the × × attribute of the product". The remaining respondents were permitted to participate in the main experiment. Then they saw an online shopping assistance communication between the service agent and a consumer. They were invited to imagine that the consumer was themselves and answer the questions based on the communication. To encourage participants' engagement, apart from rewarding monetary compensation through the paid service of http://www.wjx.cn, the findings of this research will be emailed to the participants who had left their email addresses after the research was published.

In scenarios 1 and 2, product functional attributes were emphasized. A description of an air fryer or a coat was presented randomly in the pre-experiment stage. Correspondingly, a communication between the service agent and the participant about the cooking function of the air fryer or about the insulating power of the coat was displayed in the main-experiment stage. At the beginning of the main-experiment stage, participants in scenario 1 were informed that the service agent communicating with them was an AI chatbot, and the ones in scenario 2 were informed that the service agent interacting with them was a HFLE. The role of agent type in customers' responses was emphasized in a similar way in some recent literature (Wien and Peluso, 2021; Giroux et al., 2022; Longoni and Cian, 2022), and we followed these studies: in order to manipulate service agent type, participants were explicitly told the type of agent (AI vs. Human) before the experiment in our study.

In scenarios 3 and 4, product experiential attributes were focused on. A description of a perfume or a coat was presented randomly in the pre-experiment stage. Correspondingly, in the main-experiment stage, a communication between the service agent and the participant about the scent of the perfume or the visual effect of the coat was displayed. Before the presentation of the communication, participants in scenario 3 were informed that the service agent was an AI chatbot, and the ones in scenario 4 were informed that the service agent was a HFLE.

Each participant was invited to read the communication carefully and rated his/her satisfaction, perception of information quality, perception of waiting time, pleasure and arousal based on the shopping assistance service, using a 7-point Likert scale. At the end of the experiment, the participants were required to rate the attribute type, using a single-item scale adopted by Baltas et al. (2017) (See in Appendix B). The attribute type ratings were anchored by 1-experiential and 7-functional.

A total of 567 participants completed the experiment. In total, 28.9% of the participants were male and 71.1% were female. The majority were of young age, with 87.8% of the participants below 35 years. Approximately 78% of the participants had a bachelor's degree. Regarding participants' monthly expense, 29.3% of the participants spent less than 2,000 RMB in a month, and 36.9% of the participants spent more than 3,000 RMB in a month.

[1] The detailed description of the scenarios used in the experiments are available under the following link (93 pages in two files, with screenshots of every single step the participants can encounter, with the original Chinese text and translation) https://figshare.com/s/8221351db2bea0cd56d1.

4. Results

4.1. Manipulation check

Prior to testing hypotheses, a manipulation check was conducted to examine whether the described attribute was identified as a functional attribute. At the end of the experiment, participants were asked to perceive the attribute type described in the presented scenario, by rating on a single-item scale used in pretest (1-experiential, 7-functional) (Baltas et al., 2017). One-sample t-tests (Puzakova et al., 2013) revealed that participants in scenario 1 and 2 classified the cooking function of an air fryer and the insulating power of coat as functional attributes more ($M_{\text{cooking function}} = 4.89$, $SD_{\text{cooking function}} = 1.533$, $t(166)_{\text{diff from 4}} = 7.522$, $P < 0.001$; $M_{\text{insulating power}} = 4.88$, $SD_{\text{insulating power}} = 1.577$, $t(132)_{\text{diff from 4}} = 6.435$, $P < 0.001$)). In addition, participants in scenario 3 and 4 categorized the scent of perfume and the visual effect of a coat as experiential attributes ($M_{\text{scent}} = 2.53$, $SD_{\text{scent}} = 1.169$, $t(138)_{\text{diff from 4}} = -14.801$, $P < 0.001$; $M_{\text{visual}} = 2.97$, $SD_{\text{visual}} = 1.441$, $t(127)_{\text{diff from 4}} = -8.904$, $P < 0.001$).

4.2. Reliability and validity tests

Before testing the hypotheses of this study, reliability and validity tests were conducted on each construct. The results are shown in Table 2 and Table 3. The Cronbach's Alpha of each construct ranged from 0.793 to 0.886, exceeding the recommended 0.7 and suggesting good reliability (Nunally, 1978). With regard to the convergent validity, the average variance extracted (AVE) value of the constructs ranged from 0.670 to 0.899, exceeding the acceptable level of 0.5, and the loading of each item was over the 0.7 cut-off (see Table 2), suggesting acceptable convergent validity (Bagozzi and Yi, 1988). In addition, the correlation matrices shown in Table 3 indicate that the largest correlation was 0.709, lower than the square root of AVE for each construct, demonstrating acceptable discriminant validity (Fornell and Larcker, 1981). We note here that the final construct variable values are obtained as the weighted average values of the individual item scores.

4.3. Hypotheses tests

A two-way ANCOVA was utilized to test proposed H1a and H1b. Customer satisfaction was expressed as a function of service agent type (HFLEs vs. chatbots), product attribute types (functional vs. experiential), and their interaction. Results show that there was no main effect of either service agent type ($M_{AI} = 5.394$, $SD_{AI} = 1.095$, $M_{HFLES} = 5.371$, $SD_{HFLES} = 1.159$, $F(1, 563) = 0.002$, $P = 0.965$) or product attribute type ($M_{functional} = 5.441$, $SD = 1.095$, $M_{experiential} = 5.216$, $SD = 1.161$, $F(1, 563) = 2.307$, $P = 0.129$). However, the analysis revealed a significant interaction effect between service agent type and product attribute type, $F(1, 563) = 26.796$, $P < 0.001$. When the product attribute emphasized is functional, customer satisfaction is higher if their consultations were responded to by a an AI chatbot ($M = 5.683$, $SD = 0.901$) rather than a HFLE ($M = 5.215$, $SD = 1.209$, $F(1, 298) = 14.281$, $P < 0.001$). Conversely, when the product attribute focused on is experiential, customer satisfaction is significantly lower if their consultations were responded to by an AI chatbot ($M = 5.070$, $SD = 1.201$) rather than a HFLE ($M = 5.546$, $SD = 1.077$, $F(1, 265) = 11.647$, $P = 0.001$). The results regarding between subjects effects are presented in Table 4. Thereby, *H1a and H1b was* supported.

To test H2a, H2b, H3a, H3b, H4a, H4b, H5a, and H5b, a two-way MANOVA test was conducted. For detailed results, see Table 5. Perceived information quality, perceived waiting time, pleasure, and arousal were expressed as a function of service agent type, product attribute type, and the interaction of these two variables. Results are shown in Table 5. There was no a main effect of service agent type on perceived information quality ($F(1, 563) = 1.912$, $p = 0.167$). However, the main effect of product attribute type on perceived information quality was significant ($F(1, 563) = 5.831$, $p = 0.016$). More importantly, there was a significant interaction effect between service agent type and product attribute type on perceived information quality ($F(1, 563) = 13.971$, $p < 0.001$) (see Fig. 2). When the product attribute emphasized was framed as a functional attribute, there was no difference in perceived information quality between the scenarios where participants' consultations were responded to by AI chatbots and the scenarios in which participants' consultations were responded to by HFLEs ($M_{AI} = 5.504$, $M_{HFLE} = 5.341$, $F(1, 298) = 3.408$, $P = 0.066$). However, when the product attribute focused on was framed as an experiential attribute, perceived information quality was higher when participants' consultations were responded to by HFLEs rather than AI chatbots ($M_{AI} = 5.079$, $M_{HFLE} = 5.433$, $F(1, 265) = 10.745$, $P = 0.001$). Thus, *H2a is not* supported, *while H2b is* supported.

In addition, analysis revealed that the main effect of service agent type on perceived waiting time was significant ($F(1, 563) = 8.889$, $p = 0.003$), but the main effect of product attribute type was not significant ($F(1, 563) = 1.324$, $p = 0.250$). Besides, there was an interaction effect between service agent type and product attribute type on perceived waiting time ($F(1, 563) = 17.715$, $p < 0.001$) (see Fig. 3). When the

Table 2
Results of reliability and validity tests.

Variables	Loadings	Mean	S.D.	Cronbach's alpha	AVE
Perceived information quality		5.346	0.834		
Completeness (COM)		5.329	1.052	0.860	0.705
COM1	0.829				
COM2	0.849				
COM3	0.856				
COM4	0.824				
Accuracy (ACC)		5.215	1.022	0.807	0.733
ACC1	0.887				
ACC2	0.840				
ACC3	0.840				
Believability (BEL)		5.447	0.936	0.823	0.741
BEL1	0.868				
BEL2	0.845				
BEL3	0.869				
Relevance (REL)		5.523	0.946	0.836	0.670
REL1	0.815				
REL2	0.817				
REL3	0.842				
REL4	0.800				
Timeliness (TI)		5.474	0.985	0.793	0.709
TI1	0.832				
TI2	0.834				
TI3	0.860				
Appropriate amount (AA)		5.058	1.019	0.817	0.735
AA1	0.907				
AA2	0.856				
AA3	0.806				
Perceived waiting time (PWT)		2.736	1.145	0.869	0.793
PWT1	0.890				
PWT2	0.885				
PWT3	0.897				
Positive emotions					
Pleasure (PLEA)		5.184	1.092	0.853	0.755
PLEA1	0.891				
PLEA2	0.873				
PLEA3	0.877				
Arousal (AR)		4.301	1.320	0.886	0.899
AR1	0.948				
AR2	0.948				
Customer Satisfaction (SA)		5.382	1.127	0.869	0.793
SA1	0.888				
SA2	0.893				
SA3	0.891				

Table 3
Correlations among the variables (Note: the diagonal elements (bold numbers) are the square root of AVE for each construct.).

	COM	ACC	BEL	REL	TI	AA	PWT	PLEA	AR	SA
COM	**0.840**									
ACC	0.637	**0.856**								
BEL	0.689	0.709	**0.861**							
REL	0.672	0.614	0.685	**0.819**						
TI	0.640	0.610	0.705	0.606	**0.842**					
AA	0.573	0.541	0.580	0.627	0.547	**0.857**				
PWT	−0.550	−0.509	−0.532	−0.522	−0.530	−0.492	**0.891**			
PLEA	0.585	0.518	0.552	0.513	0.550	0.493	−0.631	**0.869**		
AR	0.255	0.161	0.249	0.165	0.183	0.123	−0.215	0.297	**0.948**	
SA	0.680	0.630	0.700	0.699	0.643	0.708	−0.674	0.695	0.269	**0.891**

Table 4
Tests of between-subjects effects on satisfaction (Notes: SAT represents service agent type; PAT represents product attribute type.).

Independent variables	Mean square	F	p
Intercept	16326.943	13410.186	0.000
SAT	0.002	0.002	0.965
PAT	2.809	2.307	0.129
SAT*PAT	31.407	25.796	0.000

product attribute focused on was considered as functional, perceived waiting time was shorter significantly in AI chatbot service ($M = 2.443$) rather than HFLE service ($M = 3.120$, $F(1, 298) = 27.319$, $P < 0.001$). However, there was no difference found in perceived waiting time between AI chatbot service and HFLE service when the product attribute was classified as experiential ($M_{AI} = 2.731$, $M_{HFLE} = 2.616$, $F(1, 265) = 0.716$, $P = 0.398$). Thus, *H3a is* supported*, while H3b is not* supported.

Regarding pleasure, the results indicated that the main effect of service agent type ($F(1, 563) = 0.124$, $p = 0.725$) and the main effect of product attribute type ($F(1, 563) = 0.046$, $p = 0.831$) were not significant. However, there was a significant interaction effect of service agent type and product attribute type on pleasure ($F(1, 563) = 25.835$, $p < 0.001$) (see Fig. 4). When the product attribute emphasized was functional, AI chatbots lead higher pleasure than HFLEs ($M_{AI} = 5.421$, $M_{HFLE} = 4.932$, $F(1, 298) = 15.791$, $P < 0.001$), supporting *H4a*. Conversely, when the product attribute focused on was framed as an experiential attribute, the pleasure elicited by HFLEs was higher than that elicited by AI chatbots ($M_{AI} = 4.983$, $M_{HFLE} = 5.409$, $F(1, 265) = 10.493$, $P < 0.001$). Thus, *H4b is* supported.

With regard to H5a and H5b, analysis showed that service agent type ($F(1, 563) = 1.044$, $p = 0.307$) and product attribute type ($F(1, 563) = 0.888$, $p = 0.346$) did not affect arousal significantly. There was no significant interaction effect of service agent type and product attribute type on arousal ($F(1, 563) = 3.251$, $P = 0.071$) (see Fig. 5). When the product attribute emphasized was framed as a functional attribute, there was not a difference in arousal between the scenario where AI chatbots provided online assistance service and the scenario in which HFLEs offered online assistance service ($M_{AI} = 4.293$, $M_{HFLE} = 4.206$, $F(1, 298) = 0.310$, $p = 0.578$). However, if the product attribute focused on was experiential, HFLE service lead higher arousal than AI chatbot service ($M_{AI} = 4.198$, $M_{HFLE} = 4.511$, $F(1, 265) = 3.980$, $p = 0.047$). Thus, *H5a is not* supported*, while H5b is* supported.

To test H6a to H6d, a bootstrapping estimation method was implemented using SPSS Process macro (Model 7, Hayes (2018)), with 5000 bootstrapping samples. Service satisfaction served as the dependent variable. Perceived information quality, perceived waiting time, pleasure, and arousal served as parallel mediators. Service agent type (coded as a binary variable, taking the value 1 for the functional attributes and 2 for the experiential attributes) served as the independent variable and product attribute type (coded as a binary variable, taking the value 1 for chatbots and 2 for HFLEs) served as the moderator. The results revealed that service satisfaction was affected by perceived information quality ($\beta = 0.719$, $95\%CI = [0.635, 0.804]$), perceived waiting time ($\beta = -0.192$, $95\%CI = [-0.253, -0.131]$), and pleasure ($\beta = 0.226$, $95\%CI = [0.161, 0.291]$), but not by arousal ($\beta = 0.031$, $95\%CI = [-0.009, 0.070]$). More importantly, the interaction between service agent type and product attribute type exerted indirect effects on service satisfaction via perceived information quality ($\beta = 0.372$, $95\%CI = [0.175, 0.585]$), perceived waiting time ($\beta = 0.152$, $95\%CI = [0.059, 0.276]$), and pleasure ($\beta = 0.207$, $95\%CI = [0.106, 0.327]$), but not via arousal ($\beta = 0.012$, $95\%CI = [-0.003, 0.039]$). Thus, *H6a, H6b and H6c are* supported*, but H6d is rejected.*

To explore the nature of the interactive indirect effect between service agent type and product attribute type, we estimated the indirect effect of service agent type on customer satisfaction within two product attribute type conditions, respectively. (Conducted utilizing SPSS Process macro Model 4). Results are shown in Fig. 6 and Fig. 7. The results indicated that when the emphasized product attribute was framed as a

Table 5
Results of a two-way MANOVA test for H2a to H5b (Note: SAT represents service agent type, PAT represents product attribute type, F represents functional, E represents experiential, CBs represents AI chatbots, PIQ represents perceived information quality, PWT represents perceived waiting time.).

Variables		Dependent variable: PIQ		Dependent variable: PWT		Dependent variable: pleasure		Dependent variable: arousal	
		Mean (S.D)	F-value (p-value)	Mean (S.D)	F-value (p-value)	Mean (S.D)	F-value (p-value)	Mean (S.D)	F-value (p-value)
SAT	**CBs**	5.304 (0.879)	1.912 (0.167)	2.579 (0.989)	8.889** (0.003)	5.215 (1.013)	0.124 (0.725)	4.241 (1.411)	1.044 (1.307)
	HFLEs	5.385 (0.790)		2.883 (1.258)		5.156 (1.161)		4.350 (1.228)	
PAT	**F**	5.420 (0.767)	5.831* (0.016)	2.793 (1.169)	1.324 (0.250)	5.168 (1.092)	0.046 (0.831)	4.248 (1.346)	0.888 (0.346)
	E	5.262 (0.898)		2.671 (1.115)		5.203 (1.093)		4.360 (1.289)	
SAT* PAT	**CBs* F**	5.504 (0.760)	13.971*** (0.000)	2.443 (0.875)	17.715*** (0.000)	5.421 (0.816)	25.835*** (0.000)	4.293 (1.401)	3.251 (0.072)
\	**HFLEs* F**	5.341 (0.767)		3.120 (1.310)		4.932 (1.256)		4.206 (1.295)	
	CBs* E	5.079 (0.949)		2.731 (1.086)		4.983 (1.158)		4.198 (1.426)	
	HFLEs* E	5.433 (0.815)		2.616 (1.142)		5.409 (0.990)		4.511 (1.131)	

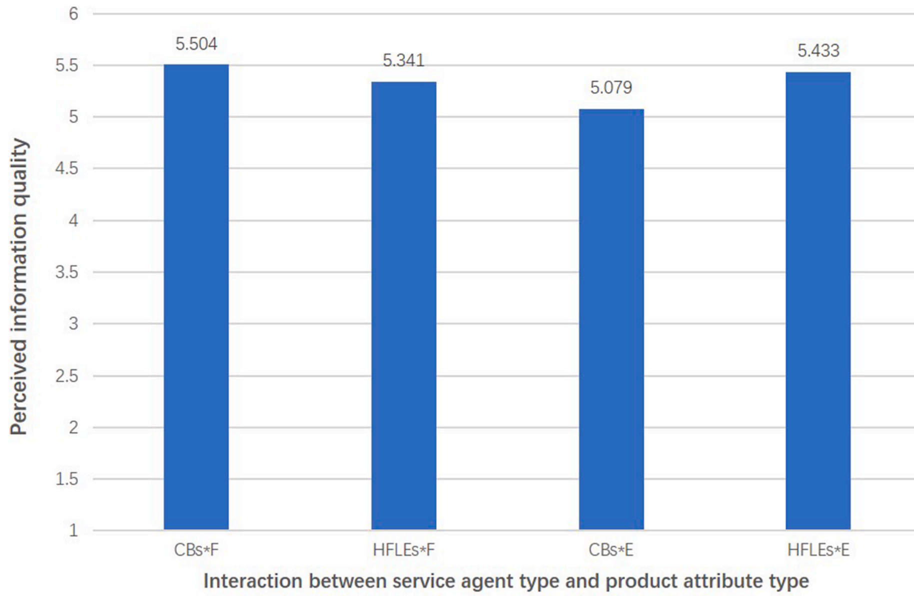


Fig. 2. Perceived information quality as a function of service agent type and product attribute type (Notes: CBs represents AI chatbots; F represents functional; E represents experiential.).

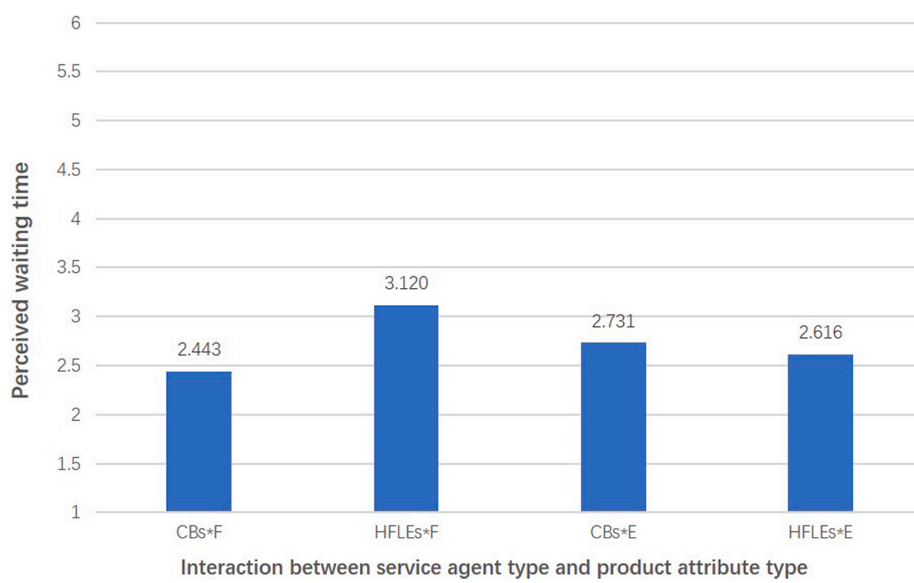


Fig. 3. Perceived waiting time as a function of service agent type and product attribute type (Notes: CBs represents AI chatbots; F represents functional; E represents experiential.).

functional attribute, AI chatbots (vs. HFLEs) resulted in higher customer satisfaction through reducing perceived waiting time ($\beta = -0.180$, 95% $CI = [-0.309, -0.074]$) and increasing pleasure ($\beta = -0.122$, 95%$CI = [-0.219, -0.049]$). However, if the product attribute focused on was experiential, HFLEs (vs. AI chatbots) performed better in elevating customer satisfaction via increasing perceived information quality ($\beta = 0.313$, 95%$CI = [0.126, 0.517]$) and pleasure ($\beta = 0.072$, 95%$CI = [0.019, 0.147]$).

To exclude the potential effect of participants' sociodemographic information on the interactive effect between service agent type and product attribute type, we tested the data again using a two-way ANCOVA (for H1a and H1b), a two-way MANOVA (for H2a to H5b), and a bootstrapping estimation method (5000 bootstrapping samples, for H6a to H6d), with participants' gender, age, educational background, and monthly expense as covariates. Results were similar to the results without the covariates. There was a main effect of service agent type on perceived waiting time ($F(1, 559) = 7.526$, $p = 0.006$), but not on perceived information quality ($F(1, 559) = 3.194$, $p = 0.074$), pleasure ($F(1, 559) = 0.000$, $p = 0.991$), and arousal ($F(1, 559) = 1.755$, $p = 0.186$). The main effect of product attribute type on perceived information quality was significant ($F(1, 559) = 4.534$, $p = 0.034$), but not significant on perceived waiting time ($F(1, 559) = 1.780$, $p = 0.183$), pleasure ($F(1, 559) = 0.272$, $p = 0.602$), and arousal ($F(1, 559) = 1.218$, $p = 0.270$). In addition, there was a main effect of service agent type on perceived waiting time ($F(1, 559) = 7.526$, $p = 0.006$), but not on perceived information quality ($F(1, 559) = 3.194$, $p = 0.074$), pleasure ($F(1, 559) = 0.000$, $p = 0.991$), and arousal ($F(1, 559) = 1.755$, $p = 0.186$). The main effect of product attribute type on perceived information quality was significant ($F(1, 559) = 4.534$, $p = 0.034$), but not significant on perceived waiting time ($F(1, 559) = 1.780$, $p = 0.183$), pleasure ($F(1, 559) = 0.272$, $p = 0.602$), and arousal ($F(1, 559) = 1.218$, $p = 0.270$). In addition, there was a significant interactive effect between

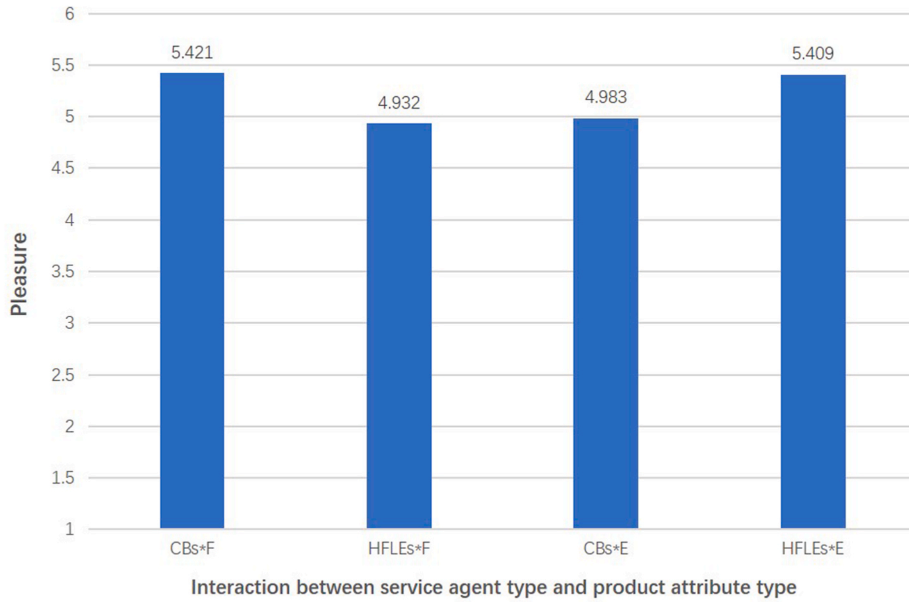


Fig. 4. Pleasure as a function of service agent type and product attribute type (Notes: CBs represents AI chatbots; F represents functional; E represents experiential).

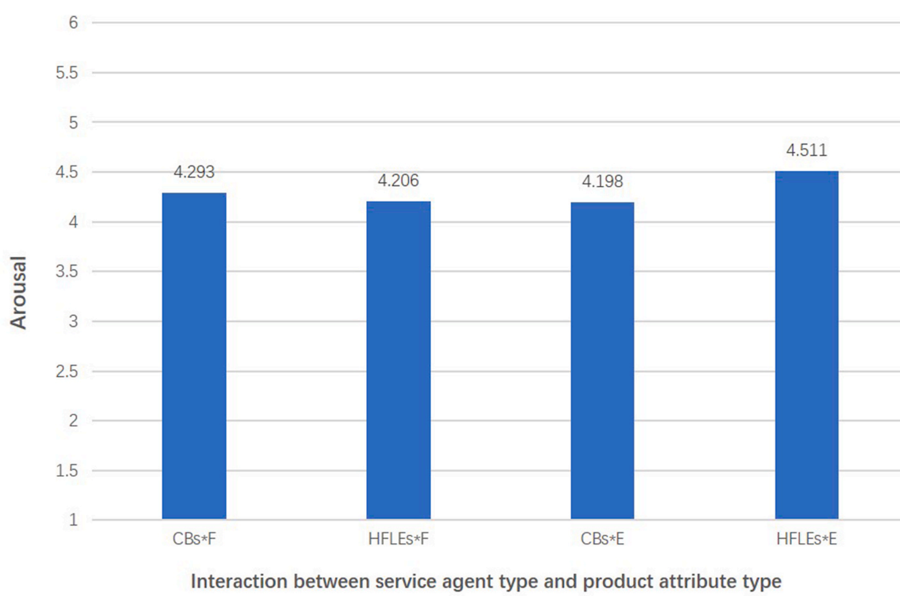


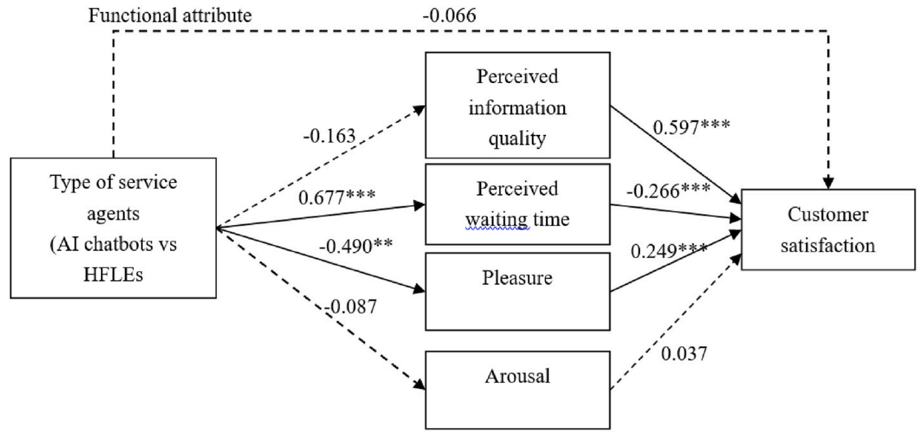
Fig. 5. Arousal as a function of service agent type and product attribute type (Notes: CBs represents AI chatbots; F represents functional; E represents experiential.).

service agent type and product attribute type on customer satisfaction ($F(1, 559) = 24.819$, $p < 0.001$), perceived information quality ($F(1, 559) = 13.070$, $p < 0.001$), perceived waiting time ($F(1, 559) = 16.749$, $p < 0.001$), and pleasure ($F(1, 559) = 24.632$, $p < 0.001$), respectively. When the attributes were functional, AI chatbots (vs. HFLEs) lead to higher customer satisfaction ($M_{AI} = 5.683$, $SD_{AI} = 0.901$, $M_{HFLE} = 5.215$, $SD_{AI} = 1.209$, $F(1, 298) = 14.281$, $p < 0.001$), lower perceived waiting time ($M_{AI} = 2.443$, $SD_{AI} = 0.875$, $M_{HFLE} = 3.120$, $SD_{AI} = 1.310$, $F(1, 298) = 27.319$, $p < 0.001$), and higher pleasure ($M_{AI} = 5.421$, $SD_{AI} = 0.816$, $M_{HFLE} = 4.932$, $SD_{AI} = 1.256$, $F(1, 298) = 15.791$, $p < 0.001$). Conversely, if the attributes were experiential, HFLEs (vs. AI chatbots) resulted in higher customer satisfaction ($M_{AI} = 5.070$, $SD_{AI} = 1.201$, $M_{HFLE} = 5.546$, $SD_{AI} = 1.077$, $F(1, 265) = 11.647$, $p < 0.001$), higher perceived information quality ($M_{AI} = 5.079$, $SD_{AI} = 0.949$, $M_{HFLE} = 5.433$, $SD_{AI} = 0.815$, $F(1, 265) = 10.745$, $p < 0.001$), higher pleasure ($M_{AI} = 4.983$, $SD_{AI} = 1.158$, $M_{HFLE} = 5.409$, $SD_{AI} = 0.990$, $F(1, 265) = 10.493$, $p < 0.001$), and higher arousal ($M_{AI} = 4.198$, $SD_{AI} = 1.426$, $M_{HFLE} = 4.511$, $SD_{AI} = 1.131$, $F(1, 265) = 3.980$, $p = 0.047$). With regard to the mediating effects of perceived information quality, perceived waiting time, pleasure, and arousal, the results indicated that the interaction between service agent type and product attribute type on customer satisfaction was mediated by perceived information quality ($\beta = 0.349$, $95\%CI = [0.151, 0.560]$), perceived waiting time ($\beta = 0.147$, $95\%CI = [0.058, 0.262]$), and pleasure ($\beta = 0.200$, $95\%CI = [0.103, 0.318]$), but not by arousal ($\beta = 0.012$, $95\%CI = [-0.004, 0.041]$).

5. Discussion and implications

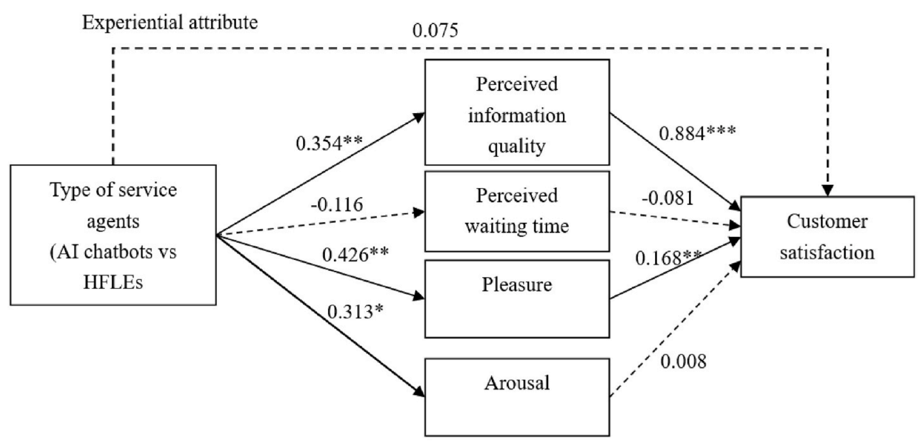
5.1. Summary and discussion of findings

The focus of this study is to complement previous research on the superiority of different service agents (AI chatbots versus human FLEs)



Indirect effect via perceived waiting time = -0.180, 95% CI = [-0.309, -0.074];
Indirect effect via pleasure = -0.122, 95% CI = [-0.219, -0.049].

Fig. 6. Impact of service agent type within the condition of product functional attribute).



Indirect effect via perceived information quality = 0.313, 95% CI = [0.126, 0.517];
Indirect effect via pleasure = 0.072, 95% CI = [0.019, 0.147].

Fig. 7. Impact of service agent type within the condition of product experiential attribute).

in online shopping assistance by comparing customer satisfaction under two types of product attributes (functional versus experiential). Extending existing literature, focusing mainly on the roles of different service agents regardless of product characteristics (Luo et al., 2019; Prentice et al., 2020), this study classifies product attributes into functional and experiential ones, between which customers' cognitive processes and affective responses would be different (Brakus et al., 2014; Sun et al., 2019; Estes et al., 2018). The combinations of service agent type and product attribute type are discussed and results from a scenario-based experiment indicate that the comparative advantages between AI chatbots and HFLEs varies across product attribute type. Specifically, when the product attributes emphasized are functional, AI chatbots lead to higher customer satisfaction than HFLEs, but when the product attributes focused on are experiential, customer satisfaction is higher if customers' consultations are responded to by HFLEs rather than AI chatbots.

Furthermore, the cognitive-affective model was introduced into this study to explain the influence mechanisms underlying the interaction effect of service agent type and product attribute type on customer satisfaction. Perceived information quality, perceived waiting time, and pleasure, three determinants of customer satisfaction, were found to be influenced by the interaction of service agent type and product agent type, but not for arousal, another dimension of positive emotion. Specifically, when the product attribute emphasized is functional, AI chatbots (vs. HFLEs) elicit higher customer satisfaction via leading to shorter perceived waiting time and higher pleasure, but they perform similarly to HFLEs in increasing perceived information quality or arousal. In contrast, when the product attribute focused on is experiential, HFLEs (vs. AI chatbots) lead to higher customer satisfaction through eliciting higher perceived information quality and pleasure, but they perform similarly to AI service robots in perceived waiting time. With regard to arousal, although HFLEs (vs. AI chatbots) perform better in eliciting arousal when the product focused on is experiential, the indirect effect of service agent type on customer satisfaction is not significant because of the negligible relationship between arousal and customer satisfaction.

Regarding to the finding that Hypothesis 2a is not supported, a possible explanation is consumers' high confidence in HFLEs' capability to provide general information. With the prevalence of E-commence, HFLEs have played the role of online service agents in the past couple of decades. Consumers' successful experience in getting useful information, including functional information, from HFLEs makes them believe that HFLEs are typically professional enough to provide general product information, or at least we cannot claim that they are inferior. As for the rejected Hypothesis 3b, the natural limitation of HFLEs' capability in the speed of response would be helpful to explain the finding. HFLEs' response speed varies across the length of the response text, which would not happen for baseline AI chatbots (Rhim et al., 2022). Although the gap of perceived waiting time between AI chatbots and HFLEs has been narrowed in the experiential scenarios, HFLEs still fail to respond to all questions immediately, not like AI chatbots. This makes HFLEs incapable of performing better in shortening perceived waiting time than AI chatbots.

In addition, there is a possible explanation for the finding that failed to support Hypothesis 5a. Arousal occurs more easily during utilitarian/functional consumption journeys compared to hedonic/experiential ones. Products with higher hedonic/experiential value induce arousal easily (i.e., excitement and cheerfulness), but products with higher utilitarian/functional value are associated more with cognitive feelings instead of arousal (Chang et al., 2014). Regarding to particular stimuli which elicit arousal, their effects would become weaker in utilitarian/functional contexts (Guido et al., 2007; Das et al., 2019). Thereby, although HFLEs (vs. AI chatbots) would be more capable to elicit high arousal in experiential contexts, this effect is weaker in functional contexts, thereby leading to no difference in arousal between two types of service agents.

With regard to the rejected Hypothesis 6d which proposed that the interactive effect between service agent type and product attribute type on customer satisfaction was mediated by arousal, there are two possible reasons. One is similar to the explanation for the rejected Hypothesis 3a. The superiority of HFLEs (vs. AI chatbots) on arousal would decrease when the product attributes emphasized are framed as functional. Another is that during online service, the effect of arousal on customer attitude or satisfaction experiences a decrease or even disappears sometimes (Lee, 2016; Cheng et al., 2020; Tueanrat et al., 2021). This also occurred in this study.

5.2. Theoretical implications

This study contributes to theoretical development in at least three important ways. First, this study is among the first to document the diverse roles of AI chatbots and HFLEs in customer satisfaction under different online shopping assistance scenarios (functional versus experiential). It is hence responding to recent calls for research on the questions whether customers value suggestions from HFLEs more than AI chatbots and how to select the best service agent types (AI or human) based on service task characteristics (Robinson et al., 2020). The related findings deepen the understanding of different service agents' superiority under different service tasks, adding new evidence to the statement that AI and human FLEs should dominate different service tasks because of their distinguishing features and service capabilities (Wirtz et al., 2018).

More importantly, introducing product attribute type as a moderating factor into the research framework, this study provides new insights to the conflicting findings of previous literature regarding customer response to AI chatbot service. According to existing literature, most online customers accept AI chatbots and consider them fully responsive, absolutely neutral, more objective, and to represent a future trend (Li et al., 2020a). However, they still prefer HFLEs' service (Prentice et al., 2020) and are more likely to accept HFLEs' suggestions even when the AI chatbots are as professional and experienced as HFLEs (Luo et al., 2019). To distinguish between product experiential attributes and functional attributes, this study proves that the superiority of AI chatbots in leading to favorable customer satisfaction depend on the attribute types the AI chatbots need to respond to. Although the performance of AI chatbots is not as good as that of HFLEs when the product attributes emphasized are experiential, customers feel more satisfied towards AI chatbots if the product attributes focused on are functional.

Finally, different from existing literature which explain the difference of AI and human service performance mainly based on cognitive processes (i.e., mentalizing, self-referencing, or perceived information quality) (Wien and Peluso, 2021; Xiao and Kumar, 2021; Prentice and Nguyen, 2020), this study proves that the customer satisfaction associated with two types of service agent is determined both by customers' cognitive and affective processes. Beyond perceived information quality and perceived waiting time, pleasure is also found to explain significantly the different roles of AI chatbots and HFLEs in customer satisfaction under different service scenarios. The mediating role of perceived information quality, perceived waiting time and pleasure in the relationship between customer satisfaction and the combination of service agent type and product attribute type help to deepen our understanding about how AI chatbots and HFLEs lead to different customer responses under diverse service scenarios.

5.3. Practical implications

Beyond contributing to advancing academic literature, the findings of this study also have practical implications for the applications of AI chatbots in online shopping assistance. The variations of customer satisfaction along with the combination of service agent type and product attribute type indicate the importance of product attribute type in selecting the best service agent types (AI chatbots or HFLEs) to respond to customer consultations. The types of product attributes implied in customer consultations must be detected before companies arrange a suitable service agent to provide online shopping assistance. Specifically, HFLEs should be given a priority when customers require consultation about product experiential attributes, because compared to AI chatbots, HFLEs can make customers perceive the information as high quality more easily and lead to higher pleasure and arousal, the first two of which in turn results in higher customer satisfaction. Conversely, if customers' consultations are about product functional attributes, utilizing AI chatbots to answer customers' questions will be more efficient and cost-saving. Serviced by AI chatbots, customers normally perceive lower waiting time and feel more pleased, with similar information quality perceptions and arousal compared to being serviced by HFLEs, thereby leading to higher customer satisfaction. In addition, the limitation of AI chatbots in satisfying experiential service indicates that beyond external anthropomorphic characteristics, AI chatbots' capability to provide higher-quality personalized information and elicit customers' positive emotions needs to be increased further during companies' AI training. Finally, the disappeared effect of arousal on customer satisfaction implies that the importance of arousal needs to be reconsidered when improving the marketing effectiveness in the context of online shopping.

6. Limitations and future research

Although this is the first study to compare customer satisfaction associated with AI chatbots and HFLEs in online shopping assistance from the perspective of product attribute types, there are some limitations to this research, which can be overcome in future research. First, even though the two type of product attributes chosen by the experiment are from a utilitarian product, a hedonic product and a product containing functional and experiential attributes, which are helpful to avoid customers' cognitive and behavioral bias as highlighted by prior literature (Lehmann and O'shaughnessy, 1974; Baltas et al., 2017), the findings should not be over-generalized because they are limited to three products. More products can be incorporated into future research framework to increase the generality of the conclusions. Second, simulative interactions instead of real interactions are used to develop the experiment in this study. Although the reasonability of this approach has been confirmed widely in previous research (Holmqvist et al., 2019; Choi et al., 2019), the research could benefit from examining the roles of service agent type and product attribute type in a field setting and collecting data from real interactions in the future. Finally, only two dimensions of customers' cognitive processes are considered in this research. In fact, beyond perceived information quality and perceived waiting time, perceived interaction quality and other dimensions of service quality are also important to increase customer satisfaction (Zhou et al., 2019; Hong et al., 2020). In future research, these variables could be incorporated into the research framework to deepen the understanding of the influence mechanisms of AI chatbots and HFLEs under diverse service circumstances.

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Appendix A. The measures

Items labels with '(R)' are reverse coded.

Perceived information quality (1-strongly disagree to 7-strongly agree).

Completeness.

- This information provided by the service agent includes all necessary values.
- This information provided by the service agent is complete.
- This information provided by the service agent is sufficiently complete for my needs.
- This information provided by the service agent has sufficient breadth and depth for my decision-making.

Accuracy.

- There are few errors in the information provided by the service agent.
- The information provided by the service agent is accurate.
- The information provided by the service agent is incorrect (R).

Believability.

- This information provided by the service agent is believable.
- This information provided by the service agent is trustworthy.
- This information provided by the service agent is credible.

Relevance.

- This information provided by the service agent is useful to my decision-making.
- This information provided by the service agent is relevant to my decision-making.
- This information provided by the service agent is appropriate for my decision-making.
- This information provided by the service agent is applicable to my decision-making.

Timeliness.

- This information provided by the service agent is sufficiently current for my decision-making.
- This information provided by the service agent is sufficiently timely.
- This information provided by the service agent is sufficiently up-to-date for my decision-making.

Appropriate amount.

- This information provided by the service agent is of sufficient volume for my needs.
- The amount of information provided by the service agent does not match my needs. (R).
- The amount of information provided by the service agent is neither too much nor too little.

Perceived waiting time (1-strongly disagree to 7-strongly agree).

- The length of time I wait during the communication is appropriate (R).
- It took the length of time I expected (R).
- The length of time I spent waiting during the communication is acceptable (R).

Positive emotions (ranged from 1 to 7).

Pleasure Interacting with the service agent, I feel.

- Unhappy–happy.
- Annoyed–pleased.
- Despairing–hopeful.

Arousal Interacting with the service agent, I feel.

- Relaxed–stimulated.
- Calm–excited.

Customer satisfaction (1-strongly disagree to 7-strongly agree).

- I feel satisfied with the performance of the service agent.
- The performance of the service agent has met my expectations.
- My satisfaction level with the performance of the service agent is quite close to my ideal online shopping assistance service.

Appendix B. Manipulation check questions

Scenarios 1 and 2

- Option 1 Air fryer

In your opinion, is the cooking function of the air fryer discussed in the communication as an experiential attribute or a functional attribute? Please choose a number below, with smaller values representing experiential attributes more, and larger values representing functional attributes more. (Experiential attributes are typically associated with consumers' aesthetic pleasure and entertaining experiences, referring to the attributes powerful to affect consumer sensory perception, moods, emotions and feelings. In contrast, functional attributes refer to the ones capable of serving as instruments towards fulfilling some of your objectives, especially for the tangible material objectives.)

- Option 2 Coat

In your opinion, is the insulating power of the coat discussed in the communication as an experiential attribute or a functional attribute? Please choose a number below, with smaller values representing experiential attributes more, and larger values representing functional attributes more. (Experiential attributes are typically associated with consumers' aesthetic pleasure and entertaining experiences, referring to the attributes powerful to affect consumer sensory perception, moods, emotions and feelings. In contrast, functional attributes refer to the ones capable of serving as instruments towards fulfilling some of your objectives, especially for the tangible material objectives.)

Scenarios 3 and 4

- Option 1 Perfume

In your opinion, is the scent of the perfume discussed in the communication as an experiential attribute or a functional attribute?

Please choose a number below, with smaller values representing experiential attributes more, and larger values representing functional attributes more. (Experiential attributes are typically associated with consumers' aesthetic pleasure and entertaining experiences, referring to the attributes powerful to affect consumer sensory perception, moods, emotions and feelings. In contrast, functional attributes refer to the ones capable of serving as instruments towards fulfilling some of your objectives, especially for the tangible material objectives.)

- Option 2 Coat

In your opinion, is the visual effect of the coat discussed in the communication as an experiential attribute or a functional attribute? Please choose a number below, with smaller values representing experiential attributes more, and larger values representing functional attributes more. (Experiential attributes are typically associated with consumers' aesthetic pleasure and entertaining experiences, referring to the attributes powerful to affect consumer sensory perception, moods, emotions and feelings. In contrast, functional attributes refer to the ones capable of serving as instruments towards fulfilling some of your objectives, especially for the tangible material objectives.)

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