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Whether to trust chatbots: Applying the event-related approach to understand consumers' emotional experiences in interactions with chatbots in e-commerce

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ABSTRACT

Chatbots can be used in marketing services to substantially improve the consumer experience. Based on cognitive appraisal theory, this study applied an event-related potential (ERP) approach to investigate consumers' emotional experiences and consumer trust in passive interaction with chatbots versus humans, taking into account objective or subjective tasks in e-commerce. The results showed that chatbot (vs. human) service interactions automatically drew more consumer attention at the subconscious stage (i.e., a larger P2); consumers purposefully allocated more resources to regulate the negative emotions elicited by chatbots at the conscious stage (i.e., a larger LPP); and there was a lower trust in chatbots than in humans. Moreover, under subjective tasks, the differences between chatbots and human agents in emotional experience (as reflected by LPP) and trust were amplified. The findings will encourage e-retailers to improve the emotional service experience of their chatbots and prioritize the application of chatbots for objective tasks in customer service.

1. Introduction

Given the growing ubiquity of artificial intelligence (AI) in the consumer domain, diverse interactions between consumers and AI in the digitized world reconfigure many service encounters (Ostrom et al., 2019; Schmitt, 2019). In e-commerce, AI agents for customer services (chatbots) are systems designed to communicate with human users and provide real-time customer services (Schuetzler et al., 2020; Adam et al., 2021). They can simulate human interaction through text chats or voice commands (Luo et al., 2019), and customers can communicate with chatbots to obtain information (e.g., product details) or assistance (e.g., solving technical problems) (Adam et al., 2021; Song et al., 2022).

Although some functions of chatbots are similar to those of humans, the interaction between consumers and chatbots is a new service experience (Kunz et al., 2019; Huang and Rust, 2018). In particular, the affective and emotional aspects of consumer experience are essential elements in the interaction with AI-based self-service technology (Chen et al., 2021). Moreover, the coexistence of human agents and AI chatbots is and will continue to be an essential feature of customer service (Longoni et al., 2019). And consumers have different levels of trust between chatbots and human agents (e.g., Yun et al., 2021). Therefore, it is necessary to explore what differences exist in consumers' emotional experiences when they interact with chatbots and human agents, and how emotional experiences impact consumer trust in chatbots or human agents. Understanding these questions could help marketers improve the efficiency of cooperation between chatbots and human workers in e-commerce.

Previous studies have examined different consumer attitudes toward AI agents and humans by using various explanations from different perspectives, such as uniqueness (Longoni et al., 2019), expectations discrepancy (Garvey et al., 2022), and evolution (Yun et al., 2021). Most previous explanations are suitable for scenarios in which consumers actively choose whether to use AI. However, in real e-commerce, consumers passively accept AI services from chatbots, and they are unable to choose the service category. For example, when consumers consult about pre-sale matters on Taobao.com, a chatbot (not a human) often

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provides AI services first, and consumers have to interact with the AI agent passively (Song et al., 2022). Therefore, the perspective of interactive experience offers new insight into consumer trust in chatbot/human services (Chung et al., 2020; Zhao and Wang, 2021). Moreover, Cognitive Appraisal Theory (CAT) can reflect the evaluation of service experience and individuals' responses through the two stages of appraisal and coping. Among them, the coping process for consumer reaction can be used in the current study. Based on CAT, this study aims to investigate how consumers perceive the interactive experience with chatbot/human services and how interactive experiences impact consumer trust in chatbot/human services.

Another interest of this study lies in the moderating effect of task type (task subjectivity and objectivity) on chatbot/human service experience and consumer trust. Previous studies suggest that attitudes, whether consumers are averse to or prefer AI services, vary significantly with perceived task objectivity or subjectivity (Logg et al., 2019; Yeomans et al., 2019; Castelo et al., 2019,b). In e-commerce, consulted questions about products, businesses, and services can also be divided into subjective or objective questions according to whether they require intuition-based or rule-based analysis (Inbar et al., 2010; Castelo et al., 2019,b). However, it is unclear how task type in e-commerce affects consumers' interactive experience and trust in chatbot/human services.

As for consumer experience evaluation, Tiberio et al. (2013) summarized and introduced psychological, behavioral, and physiological measures for interaction with AI. However, the psychological or behavioral approaches may not yield cognitive information in the subconscious domain (Wang et al., 2016). Event-Related Potential (ERP), a non-invasive brain-scan technique, has been recently used to study underlying consumer responses to human and AI agents from an electrophysiological time course perspective (Chung et al., 2020). Moreover, consumers' emotional experiences toward different stimuli are reflected by varying human brain responses (Pozharliev et al., 2015; Zhao and Wang, 2021). Therefore, the ERP approach can be used in the present study to further investigate the subconscious and conscious processes associated with consumers' emotional experience with chatbot/human service interactions in e-commerce.

In short, a pilot behavioral study with 179 participants and an ERP study with 35 participants were conducted to investigate the emotional experiences and consumer trust in the process of interaction with chatbots/human services, taking into account the moderating effect of task type (objective vs. subjective). This study contributes to the understanding of service experiences in chatbot/human service interaction and has managerial implications for e-retailers by aiding them to guide how or when to deploy chatbots in e-commerce.

2. Theoretical background

2.1. Chatbot service and human service

AI agents (such as chatbots) are increasingly viable options to replace human representatives who indirectly manage products and services to customers (Garvey et al., 2022; Song et al., 2022). The potential of chatbots is well acknowledged, and consumer attitudes toward chatbots have recently drawn attention in the academic circles. Some studies have explored factors influencing consumer trust in chatbots in e-commerce (Yen and Chiang, 2021; Cheng et al., 2022). For example, Cheng et al. (2022) suggested that the empathy and friendliness of chatbots positively impact consumer trust. Yen and Chiang (2021) constructed a chatbot trust model and demonstrated that credibility, competence, social presence, and informativeness all influence consumers' trust and purchase intention. However, few studies have explored the effect of consumer interaction with chatbots on consumer trust.

Furthermore, many previous studies have investigated different consumer attitudes and behaviors toward AI (such as chatbots) and humans (e.g., Granulo et al., 2021; Yun et al., 2021; Dietvorst et al., 2018). Compared with their attitudes toward humans, consumers have two different attitudes toward AI: algorithm aversion (Dietvorst et al., 2014, 2018), and algorithm appreciation (Logg et al., 2019). Dietvorst et al. (2014) suggested that people are reluctant to use AI services, even when they see AI outperforming humans. Yet, Logg et al. (2019) indicated that people have a propensity to opt for algorithmic advice over human advice. Consumer preference for humans or AI agents was affected by context. For example, consumers prefer human services in higher (vs. lower) symbolic consumption contexts than AI services (Granulo et al., 2021). The utilitarian/hedonic attribute trade-off also influences consumer preference for or resistance to AI services (Longoni and Cian, 2022). Chatbots are typical AI agents in e-commerce, and consumers may have different attitudes (e.g., algorithm aversion and algorithm appreciation) towards them in e-commerce. The inconsistent consumer attitudes towards chatbots therefore make it necessary to explore the processes of consumer interaction with chatbot/human services.

Moreover, various perspectives have been adopted to explain consumer preferences for and attitudes toward AI and human services (Longoni et al., 2019; Yun et al., 2021; Garvey et al., 2022; Song et al., 2022). For example, Longoni et al. (2019) suggested that uniqueness neglect drives consumer resistance to AI services. Yun et al. (2021) used evolution theory to explain consumers' interactions with medical AI and a human doctor. Garvey et al. (2022) discovered that AI agents (vs. human agents) asymmetrically alter the effects of outcome expectation discrepancies upon purchase, satisfaction, and re-engagement intentions. Table 1 of Appendix 1 summarizes the major findings from these empirical studies on AI services (including chatbots). In the current study, we extend this stream of literature by investigating the differences of consumer trust in chatbot/human services from the perspectives of emotional experience using a neuroscience method.

2.2. Cognitive appraisal theory

Cognitive Appraisal Theory (CAT) proposes that emotions as mental states are evoked on the basis of evaluations of personally relevant stimuli or events (Lazarus, 1991; Smith and Ellsworth, 1985). It focuses on cognitive emotion and suggests that emotion emerges from the appraisal of an event or experience related to personal motives, goals, and needs (Lazarus, 1991; Roseman and Smith, 2001). The model of CAT includes two cognitive stages: appraisal and coping, and depicts how "appraisals" of stimuli evoke different emotions and how emotions subsequently influence responsive behavior (Ying et al., 2021).

Previous studies have applied CAT to explain implicating emotions from a person's cognitive appraisal of a particular experience and their effects on the coping stage (Choi and Choi, 2019; Li et al., 2021). For example, Choi and Choi (2019) revealed that enhancing perceived experiential value related to consumers' cognitive appraisal of tourism destinations can elicit positive emotions, leading to immediate and favorable behavioral intentions. Negative experiences (e.g., service delays) in consumer service elicit negative emotions (e.g., anger and worry), which generate subsequent adverse outcomes, such as declining customer loyalty (Li et al., 2021). Although CAT has been used to examine various services (such as luxury shopping experiences) (Kim et al., 2016; Watson and Spence, 2007) or tourism experiences (Lee and Lee, 2021; Munanura et al., 2021), to our knowledge, no research has used CAT to investigate emotional experience and consumer trust in interaction with chatbot services. As interaction with chatbots is a new service experience (Huang and Rust, 2018; Kunz et al., 2019), CAT may be seen as a basis for how we understand the consumer cognitive process in chatbot interactions. The current study in turn provides neuroscience evidence for the appraisal and coping processes of CAT.

2.3. Emotional experience in chatbot/human service interaction

Customer experience is thought to comprise consumers' non-deliberate and spontaneous responses to offering-related stimuli

Table 1
Mean (amplitudes) of the ERP components and TRs in the ERP study.

			P2 (125–200 ms)	LPP (400–600 ms)	TRs
Service category		**Chatbot service**	2.754 (0.702)	2.942 (0.445)	0.663 (0.025)
		Human service	0.571 (0.643)	1.180 (0.497)	0.766 (0.029)
Task type		**Objective task**	1.713 (0.651)	2.133 (0.436)	0.909 (0.030)
		Subjective task	1.611 (0.675)	1.989 (0.476)	0.521 (0.042)
Task type	**Objective task**	**Chatbot service**	2.681 (0.711)	2.714 (0.485)	0.891 (0.032)
		Human service	0.746 (0.648)	1.552 (0.481)	0.926 (0.029)
	Subjective task	**Chatbot service**	2.828 (0.726)	3.169 (0.478)	0.435 (0.044)
		Human service	0.395 (0.671)	0.808 (0.577)	0.606 (0.048)

Note: The number in the first row of every cell is the mean value. The standard error (S.E.) of each average is displayed in parentheses. TRs stands for trusting rates.

throughout the customer journey (Becker and Jaakkola, 2020). Although consumer experience has recently received much attention in the marketing literature, the topic still requires further conceptual development and empirical research (Cachero-Martínez and Vázquez-Casielles, 2021; Moore et al., 2022). Moreover, many consumer-oriented technologies (i.e., AI technology, Virtual Reality) are creating novel opportunities and challenges for customers (Chong et al., 2021), which calls for a more holistic understanding of consumer experience to address the complexities of the ever-changing consumption environment.

Emotional aspects, such as consumer expectation, motivation, and mood are a major perspective for investigating the dynamic and subjective consumer experience (Chen et al., 2021). Emotions that consumers have in consumer interaction tend to be memorable and influence consumers' behavioral intentions (Choi and Choi, 2019; Dasu and Chase, 2010; Li et al., 2021). Emotional experience plays an important role in interactive communication and is a central element in the understanding of customer experience and behavior (Mauss et al., 2005). According to CAT, the appraisal of a special service experience can evoke emotions, which further influence individual responses (Choi and Choi, 2019; Li et al., 2021). For chatbot service, customer emotion is an essential evaluation process to determine customers' attitudes toward chatbots (Chi et al., 2020). This study explores the differences of consumers' emotional experiences when they interact with chatbots and human agents.

2.4. Consumer trust in chatbot/human services

Trust can be recognized as a belief and an expectation that another party will behave in a credible or benevolent manner (Doney and Cannon, 1997). Consumer trust in AI agents (such as chatbots) can be extended from interpersonal trust and seen as the extent to which a consumer is confident in and willing to act on the basis of the actions or recommendations of an AI agent (Madsen and Gregor, 2000). Moreover, consumer trust in AI agents is considered the main indicator of acceptance (Gaudiello et al., 2016). Recent literature on chatbot trust has mainly concentrated on the factors influencing consumer trust in chatbot services (Cheng et al., 2022; Yen and Chiang, 2021) (see Table 1 of Appendix 1 for a summary of trust in AI services (such as chatbots). For example, Mostafa and Kasamani (2022) explored the antecedents and consequences of chatbot trust and found that there were three factors (i.e., compatibility, perceived ease of use, and social influence). And a few of them have paid attention to the role of emotion on trust in chatbots (Rodgers et al., 2021; Gkinko and Elbanna, 2022).

Previous studies have begun to investigate the differences in consumers' trust in or acceptance of AI (e.g., chatbots) and human agents (e.g., Granulo et al., 2021; Yun et al., 2021; Dietvorst et al., 2018). However, these prior findings are not consistent. For example, Dietvorst et al. (2014) suggested that people are reluctant to use AI agents, even when consumers see AI outperforming humans, which is known as algorithm aversion. Nevertheless, counter to the conclusion of algorithm aversion, Logg et al. (2019) suggested that people rely more on algorithmic advice than on human advice, which is termed as algorithm appreciation. However, there are still scant consumer trust studies that investigate the emotional experience when participants passively interact with chatbots or human agents (Zhao and Wang, 2021). Based on CAT, consumer attitudes toward a service provider can be influenced by consumers' emotional feelings (Choi and Choi, 2019; Li et al., 2021). Understanding subconscious and conscious perceptual mechanisms of emotional experience that underlie consumers' interaction with chatbot/human services might facilitate the examination of why people trust or mistrust chatbots.

2.5. The application of ERP in chatbot/human service interaction

ERP is the electrophysiological brain signal associated with neural responses to an event (Dietrich et al., 2001), which can be used to explore consumers' subconscious and conscious evaluations and behavioral reactions to specific stimuli from the perspective of an electrophysiological time course (Wang et al., 2020; Zhao and Wang, 2021). For example, Zhao and Wang (2021) used the ERP experiment to analyze the neural mechanisms of consumers' emotional involvement in the service provision process, and explain the effect of emotion on consumer attitude or behavior. With the application of ERP in AI service perception, many ERP components can be used to evaluate AI agents and effectively infer whether participants trust them (de Visser et al., 2018; Chung et al., 2020). Therefore, the ERP method can incorporate neural mechanisms in the research of consumer perception and response to chatbot/human service interaction.

Furthermore, ERP components (i.e., P2, P3, and LPP) can reflect the initial sensory encoding and sophisticated processing of emotional stimuli (Schupp et al., 2000, 2003, 2007; Pozharliev et al., 2015). Therefore, in the present study, the emotional experiences in chatbot/human service interaction can be measured by the ERP method, and ERP components can reflect the subconscious and conscious evaluation processes for chatbot/human service experience. Moreover, the ERP method may help us better understand the underlying neural mechanisms of the appraisal and coping processes in CAT.

3. Hypotheses

3.1. Consumers' emotional experience in chatbot/human service interaction

Consumers struggle to feel the same emotional experience toward AI interaction as they would do toward human interaction (Yun et al., 2021; Castelo et al., 2019,b). For example, unlike human service, AI service interactions activate consumers' apathetic emotions, reflecting consumers' negative emotional energy toward AI (Yun et al., 2021). In the present study, consumers might expect humans more than chatbots when they want to ask questions before making an online purchase decision because chatbots disregard consumer uniqueness (Longoni et al., 2019) or lack empathetic intelligence (Huang and Rust, 2018). Therefore, consumers perceive more negative emotions in chatbot service interaction than in human service interaction.

Previous ERP experimental results have shown that the amplitude of

ERP components is significantly different under the conditions of positive and negative emotional stimulations (Holmes et al., 2003). When subjects are exposed to positive or negative stimuli rather than neutral stimuli, an enhanced P2 (a positive component with a peak latency from 100 ms to 200 ms) amplitude is observed, which reflects the subconscious assessment of stimuli with automatic selective attention (Herbert et al., 2006; Lin et al., 2015; Yang et al., 2012). Moreover, negative stimuli can recruit attention resources more automatically and thus elicit a larger P2 amplitude than positive stimuli (Yang et al., 2012; Jin et al., 2017). As previously discussed, chatbot service interaction can be regarded as an emotional stimulus. Hence, we speculate that the enhanced P2 amplitude can be evoked by chatbot service experiences, which suggests an automatic attentional bias to more negative emotional stimuli.

Furthermore, besides the automatic assessment, there is a more complex and elaborate cognitive process for emotional stimulation, which can be distinguished by ERP components (Gardener et al., 2013; Zhao and Wang, 2021). LPP (a late positive component with a peak amplitude at roughly 600 ms) is sensitive to the engagement of controlled cognitive resources related to the higher-order cognitive process, reflecting the conscious process of emotion regulation (Hajcak and Nieuwenhuis, 2006; Gardener et al., 2013; Hajcak et al., 2010; MacLeod et al., 2017). The amplitudes of LPP evoked by positive and negative emotional stimuli are positively related to motivated attention and emotional regulation of affective evaluation (Schupp et al., 2000; Hajcak and Nieuwenhuis, 2006). Moreover, relative to positive emotions, individuals pay more cognitive resources to regulate negative emotions on the basis of the LPP evidence (Norris and Wu, 2021). Thus, given the emotional sensitivity of LPP, we propose that enhanced LPP represents the emotional regulation process for emotional stimuli in the conscious stage. As discussed previously, the interaction with chatbots is regarded as a more negative emotional experience than that with humans. Hence, we speculate that a more prominent LPP component is evoked by chatbots than humans, which reflects that consumers must pay more resources to regulate negative emotions evoked by chatbots at the conscious stage. Therefore, we hypothesize the following.

H1. The emotional experience with chatbot service is more negative than with human service. A larger P2 occurs at the subconscious stage with a larger LPP at the conscious stage when consumers interact with chatbots rather than humans.

3.2. Consumer trust in chatbot/human service interaction

According to CAT, an individual's emotion from his cognitive appraisal of a particular experience impacts his attitude/behavior in the coping stage (Choi and Choi, 2019). Different emotions lead to consumers' distinct coping reactions (Laros and Steenkamp, 2005). For example, negative emotions in the tourism experience generate consumers' subsequent negative attitudes, such as declining customer loyalty (Li et al., 2021). For AI services, Li et al. (2022) investigated the relationship between customers' emotions to voice-based service AI and customers' reactions, and found that emotions significantly affect customers' compliant behavior. Hence, consumers' emotional experiences from interacting with chatbot/human services can influence their attitudes in e-commerce.

As previously discussed, consumers perceive more negative emotional experiences when interacting with chatbots than with humans in e-commerce. On the basis of CAT, we speculate that negative emotions in the interaction with chatbots can lead to consumers' negative reactions. Dietvorst et al. (2014) suggested that, even when consumers see AI agents outperforming human beings, they are still unwilling to use AI agents. Therefore, in the current study, more negative emotions elicited by chatbots (vs. humans) can cause consumers to mistrust the service solutions from chatbots more than those from humans in e-commerce, even if the service solutions in the two cases are the same. That is, consumers can trust the human service output more than the chatbot service output. Therefore, we hypothesize the following.

H2. Consumer emotions evoked in chatbot/human service interaction influence consumer trust. Consumers trust human services more than chatbot services.

3.3. Moderating role of task type

Task type distinguishes between objective tasks on the basis of rule-based analysis abilities and subjective tasks on the basis of intuition abilities (Inbar et al., 2010). The subjectivity and objectivity of tasks affect customers' attitudes toward AI agents (Castelo et al., 2019; Logg et al., 2019; Yeomans et al., 2019). Consumers resist AI services more for subjective than objective tasks because they believe AI lacks the emotional ability (such as intuition and empathy) to perform subjective tasks (Inbar et al., 2010; Castelo et al., 2019). Nevertheless, based on evolution theory, humans have developed various competence skills, including cognitive and emotional capacities, to help them survive and adapt to various environments (Darwin, 1859). Thus, we assume that task type has a less impact on human service interactions than chatbot service interactions. In the current study, the consulted questions can be perceived from whether they require logical analysis or intuitive analysis (Inbar et al., 2010; Castelo et al., 2019), and divided into subjective or objective tasks. We assume that consumers' emotional experience and trust attitude change more negatively in chatbot service interactions for subjective (vs. objective) tasks in e-commerce.

ERP components have been used to reflect the underlying neural mechanisms of the interaction process with chatbot/human services. Therefore, we speculate that the moderating effect of task type can be reflected by ERP components. P2 is associated with the low-level processing of stimuli, reflecting an automatic selective attention process (Folstein and Van Petten, 2008; Olofsson et al., 2008). As a relatively new service provider which is different from traditional customer service, chatbots can be evaluated automatically at the subconscious stage. Objective and subjective tasks contain complex information and must be sophisticatedly judged with consumers' rule-based or intuition-based analysis (Inbar et al., 2010). Thus, we do not expect the P2 to reflect the moderating effect of task types. Conversely, LPP reflects sustained attention to significant stimuli under conscious control (Pozharliev et al., 2015), and individuals have more resources to evaluate the stimuli elaboratively. Thus, the moderating effect of task type on consumer's emotional evaluation can be reflected by the LPP component. As discussed previously, consumers resist AI more for subjective than objective tasks (Inbar et al., 2010; Castelo et al., 2019). Hence, compared with objective tasks, consumers perceive more negative emotions elicited from interaction with a chatbot service with subjective tasks and they pay more cognitive resources to regulate negative emotions, which can evoke a larger LPP amplitude. Therefore, we hypothesize the following.

H3. Task type plays a moderating effect on consumers' emotional experience in chatbot/human service interaction. The moderating effect of task type on consumers' emotional experience is reflected by the LPP component at the conscious stage.

H4. Task type has a moderating effect on consumers' trust in chatbot/human services.

4. Methodology

4.1. Overview of the studies

Prior to conducting the ERP study, a pilot behavioral experiment was conducted to verify the behavioral differences of consumers' emotional experience and trust attitudes between chatbot and human service interactions, while taking into account the moderating effect of task type (objective vs. subjective). After that, an ERP study was conducted to investigate the underlying neural processes associated with the emotional experience in chatbot/human service interaction. Consideration was given to the moderating effect of task type on emotional experience appraisal and trust attitude.

4.2. A pilot behavioral study

A total of 179 Chinese adult participants were recruited for a double-factor between-subject experiment in two service categories (human services vs. chatbot services) × two task types (objective task vs. subjective task). Experiment scenarios were designed to simulate buying clothes online from Taobao e-commerce (Taobao.com), and participants consulted different kinds of questions. A real female human picture was chosen for the human service category, with a real robot picture was chosen for the chatbot service category. Moreover, on the basis of Castelo et al. (2019), a questionnaire survey about task objectivity and subjectivity was conducted. The online experiment was done in April 2021. Participants were randomly assigned to one of four experimental conditions. During the pilot study, they were asked to evaluate the objectivity and subjectivity of the consulted question, emotional experiences with emotion scales, and consumer trust. The details of the pilot experiment, analysis process, and results can be seen in Appendix 2.

The pilot study found that chatbot (vs. human) service interactions ($M_{AI} = 3.958$, $SE = 0.133$; $M_{human} = 5.586$, $SE = 0.128$) elicited more negative emotional experiences ($F(1, 175) = 78.154$, $p = 0.000$), and consumers trusted the chatbot service output ($M_{AI} = 56.291$, $SE = 2.319$) less than the human service output ($M_{human} = 76.716$, $SE = 2.232$, $F(1, 175) = 40.273$, $p = 0.000$). Moreover, different consumers' emotional experiences led to different consumer trust in chatbot/human services in e-commerce. That is, the effect of service category on consumer trust was affected by consumer emotions as a complete mediator (*BBootstrap = −16.316, BootSE = 3.7033, BootCI95 [−24.181; −9.7158]*). Furthermore, task type was found to have a moderating effect on consumers' emotional experience ($F(1, 175) = 6.684$, $p = 0.011$) and consumer trust ($F(1, 175) = 10.780$, $p = 0.001$). Significantly, in subjective tasks (*simple slope* $= 9.794$, $t = 6.541$, $p = 0.000$), the effect of service category (human services vs. chatbot services) on consumers' emotional experience and trust was stronger than in objective tasks (*simple slope* $= 4.1475$, $t = 2.1508$, $p = 0.0329$), as can be seen Table 2 of Appendix 2.

The pilot study, at the behavioral level, verified the differences between chatbot and human service interaction and explored the relationship between consumers' emotional experience and consumer trust. Furthermore, the findings preliminarily confirmed that the appraisal and coping processes (reflected by emotional experience evaluation and consumer trust) existed in the chatbot/human interaction, and CAT could underpin the processes in chatbot/human interaction.

4.3. An ERP study

The purpose of the ERP study was to investigate the underlying neural processes associated with consumers' emotional experiences in chatbot/human service interaction through the neuroscience method. On the basis of CAT, we post that the subconscious and conscious appraisal processes of chatbot/human emotional experiences can be separately reflected in P2 and LPP components, with the moderating effect of task type only being reflected by the LPP component. Moreover, we investigated participants' trust attitudes toward chatbot and human services in the coping process.

4.3.1. Participants and design

A total of 35 healthy students ($M_{age} = 21.43 \pm 2.32$ years, 18 females and 17 males) from Shanghai International Studies University were recruited to participate in the current experiment. Each participant had experience in interacting with human or chatbot services in e-commerce. All participants were right-handed native Chinese speakers without a history of neurological and psychological defects and had normal or corrected to normal vision. As the chatbot was a relatively new customer service technology, the difference in chatbot literacy between college students and the general public may not differ substantially, which could be supported by the results in the current pilot study. Moreover, college students were more likely to engage in emerging AI systems (Song and Kim, 2021), and their initial feedback on chatbots had certain representativeness. Therefore, this sample of college students in the ERP experiment was relatively suitable. This ERP study was approved by the Internal Review Board of the Laboratory for Brain and Cognitive Behavioral Neuroscience of Shanghai International Studies University, and was conducted in May 2021. Written informed consent was circularized from all the subjects. Participants were rewarded 35–40 Chinese Yuan (CNY) for their time after the experiment. In addition, the reliability of sample size was estimated using G*Power software, and the results revealed that a sample of 35 participants could detect the effects with $\eta p^2 \geq 0.24$ (statistic power = 0.80).

To prove the hypotheses proposed above, a 2 (service category) × 2 (task type) within-subjects design was employed. Considering that college students were familiar with headsets, which were frequently purchased online and had the characteristics of utilitarian and hedonic products (Lu et al., 2016), the online consultation service experience with headsets was selected as the experimental situation in this experiment. Each trial of the ERP experiment included task stimuli (objective or subjective consulted questions), customer service stimuli (chatbots or human agents), and service consequence stimuli (answers to the questions). There were 80 conditions (2 types of task × 20 questions × 2 service categories), and each condition was superimposed two times, with a total of 160 trials.

4.3.2. Stimuli

Eighty-four pairs of consulted questions and answers were gathered about headset product questions that consumers would ask about before making online purchases on Taobao.com. All the answers gathered were positive feedback to rule out the influence of success or failure factors. Focus group discussions were conducted to test individuals' familiarity with the online counseling tasks and their objectivity (or subjectivity) by judging whether intuition-based or rule-based analysis was required or not (Inbar et al., 2010). Ultimately, 40 questions were confirmed, including 20 objective questions (e.g., Does the headset have a microphone?) and 20 subjective questions (e.g., Is it comfortable when worn?). Moreover, according to the method of Castelo et al. (2019), 20 objective questions ($M_{objective} = 1.5529$, $SE = 0.1034$) were perceived as less subjective than the 20 subjective questions ($M_{subjective} = 7.2843$, $SE = 0.2666$, $t(34) = -22.451$, $p = 0.000$).

Considering that real human customer services in e-commerce are mainly provided by females, a female cartoon-like service image was selected as the human service stimulus for the human service category. To take into account the image of chatbots in e-commerce in reality and avoid the effect of the Uncanny Valley (Castelo et al., 2019), a like-intelligent robot service image (not human likeness) was selected as the chatbot stimulus for the chatbot service category,. The service consequence stimuli included the chatbot (or human) picture of customer service and the consequence of answering the objective (or subjective) questions. Moreover, given that brain activities are intricate and sensitive (Wang et al., 2016), short words (less than eight characters) were used to control the length of characters in each question and answer.

4.3.3. Procedure

Participants were comfortably seated in an electrically shielded and sound-proof room during the ERP experiment. And, they were provided an instruction that "Imagine you are looking to buy a pair of headphones on Taobao.com, and you have some questions (reflected by S1) to consult online customer service to further understand the headset information. And then, a chatbot or a human agent will provide service to you, which was reflected by S2. After that, the service consequences (reflected by S3) are presented as feedback." Participants were asked to press number 1 or 3 on the keypad to express whether they trusted or distrusted the service consequence. The response-to-hand assignments were counter-balanced across the participants. Each participant completed five practice trials to be familiar with the task before the formal experiment.

The stimuli were presented using E-Prime 3.0 software (PST, Psychology Software Tools Inc.). The formal experiment was composed of four blocks, each containing 40 trials, and the ordering of trials was randomized in the whole experiment. Each trial began with a fixation for 400–600 ms, followed by the stimulus of objective (or subjective) questions (S1) for 1500 ms. Then, there was an interval with a random duration of 400–600 ms, after which the chatbot (or human) service stimulus (S2) showed for 1500 ms. Next, with a random interval of 400–600 ms, the service consequence (S3) was presented until a response was made. Finally, an inter-trial interval of 800–1000 ms followed by behavior feedback was presented. Fig. 1 presents a single trial procedure in the ERP experiment. Participants were able to rest for several minutes after each block.

4.3.4. EEG recording and analysis

The EEG data were recorded (bandpass 0.1 Hz −100Hz, sampling rate 500Hz) using an ActiCap system (Brain Products GmbH, Gilching, Germany), with 32 A g/AgCl electrodes placed according to the 10/20 international system (Committee, 1994). The ground electrode was placed before Fz, with the reference electrode located at FCz. We kept electrode impedances below 10 kΩ throughout the experiment.

EEG data were analyzed using EEGLAB and ERPLAB. EEG recordings were corrected using a regression-based method proposed by Semlitsch et al. (1986), re-referenced to the average of the mastoid electrodes, and digitally filtered with a bandpass of 0.1–30 Hz l (24dB/Octave) (Luck, 2014). The EEG recordings were extracted between −200 ms and 800 ms time-locked to the onset of S2, with a 200 ms pre-stimulus as the baseline. Trials exceeding ±100μv were excluded.

We could compare the P2 and N2 components elicited by chatbot/human services in S2. Based on a visual inspection of the grand average waveforms (as shown in Fig. 2), the time window of 125–200 ms after the onset of S2 was selected for P2 with 400–600 ms for LPP. Moreover, according to the guidelines given by Luck (2014), eight electrodes (F3, F4, C3, C4, Fz, Cz, FC1, FC2) were selected for P2 analysis, with six electrodes (P3, P4, Pz, CP1, CP2, and POz) for LPP analysis. Repeated measure analyses of variance (ANOVAs) were conducted separately for P2 and LPP. Simple effect analyses were conducted when the interactive effect was significant.

4.3.5. Results

ERP results for consumers' emotional experience. The mean P2 amplitude (125–200 ms) was analyzed by three-way 2 (task type) × 2 (service category) × 8 (electrode) repeated ANOVA. The results (as seen in Tables 1 and 2) showed that chatbot service evoked a larger P2 amplitude than human service. However, the main effect of task type and the interaction between service category and task type was not significant. Furthermore, the mean LPP amplitude (400–600 ms) was analyzed using three-way 2 (task type) × 2 (service category) × 6 (electrode) repeated ANOVA. The results (as seen in Tables 1 and 2) showed that chatbots induced a bigger LPP amplitude than humans, with no notable main effect of task type. Moreover, a significant interactive effect between task type and service category was found (as seen in Tables 1 and 2). Under the objective task conditions, the LPP amplitude induced by chatbot service was more positive than that induced by human service ($p = 0.009$). Under the subjective task conditions, the LPP amplitude induced by chatbot service was also more positive than that induced by human service ($p = 0.000$). More importantly, the differentiated LPP amplitude between chatbot and human services was significantly larger in the subjective task ($M = -2.361$, $SE = 0.464$) than in the objective task ($M = -1.162$, $SE = 0.417$) according to paired-samples T-test ($t(34) = 2.386$, $p = 0.023$).

We used the ERP components of P2 and LPP to explore the subconscious and conscious appraisal processes for chatbot/human service experience in CAT. With the results in the pilot study that consumers perceived more negative emotions when interacting with chatbot (vs. human) service, the results of the ERP study showed that chatbot (vs. human) service experiences evoked a larger P2 at the subconscious stage

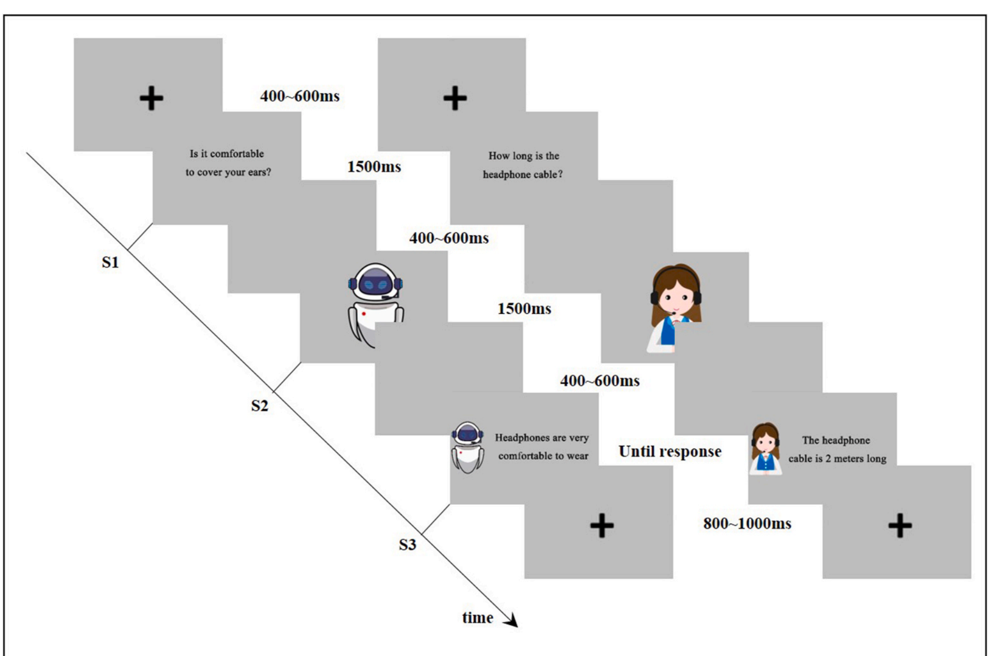

Fig. 1. Experimental task: The participants were instructed to evaluate whether they would trust the answers provided by different service categories (human service or chatbot service) in S3.

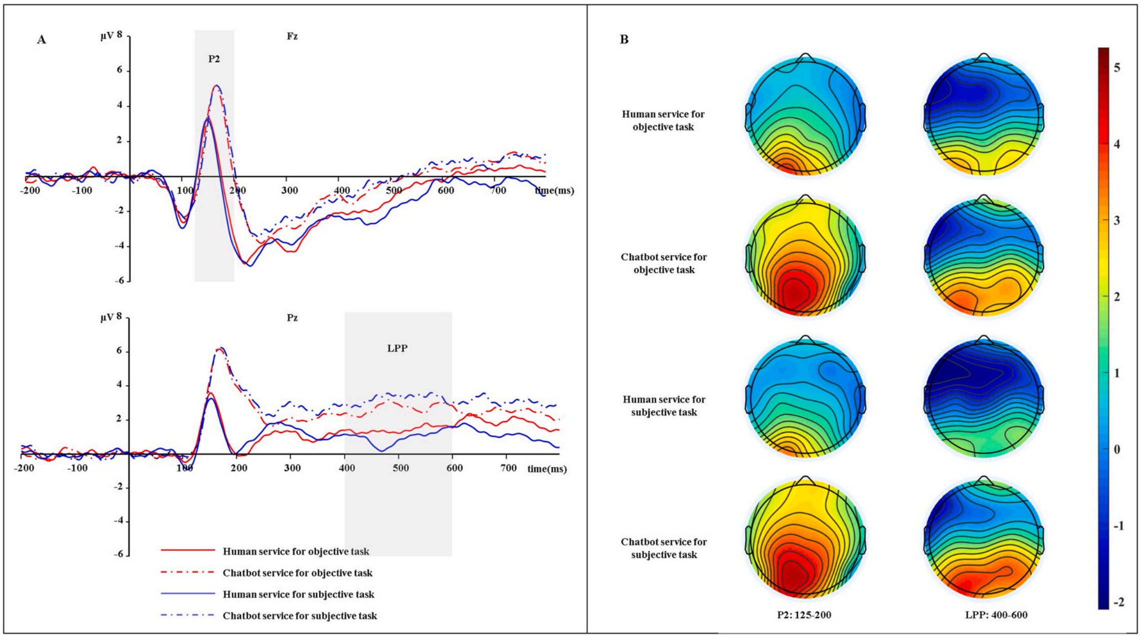

Fig. 2. Grand-average ERP waveforms (A) and brain topographic maps (B) for the P2 and LPP components.

Table 2
Results of the repeated ANOVAs on the mean (amplitudes) of P2, LPP, and TRs.

	P2 (125–200 ms)			LPP (400–600 ms)			TRs		
	F	p	η_p^2	F	p	η_p^2	F	p	η_p^2
Service Category	45.810	0.000	0.574	23.577	0.000	0.409	21.103	0.000	0.383
Task type	0.214	0.647	0.006	0.282	0.599	0.008	50.699	0.000	0.599
Service Category × Task type	1.595	0.215	0.045	5.694	0.023	0.143	15.566	0.000	0.314

Note: df = (1, 34); $p < 0.05$ is significant; η_p^2 is partial eta squared. TRs stands for trusting rates.

and a larger LPP at the conscious stage. Thus, H1 is supported. Moreover, another finding was that the effect of task type on consumers' emotional experience appraisal was only found in the LPP component at the conscious stage. Thus, H3 is supported.

Behavioral results of consumer trust. Consumer trust was reflected by the trusting rates (TRs) that participants gave in the ERP experiment. The TRs were analyzed by repeated ANOVA with factors of task type (objective task vs. subjective task) and service category (human service vs. chatbot service). The results (as seen in Tables 1 and 2) showed that human service had higher TRs than chatbot service, with higher TRs for the objective task than for the subjective task. Moreover, the interactive effect between task type and service category was significant (as seen in Tables 1 and 2). Under the objective task condition, the TR of human service was higher than that of chatbot service ($p = 0.000$). Under the subjective task condition, the TR of human service was also higher than that of chatbot service ($p = 0.000$) (see Fig. 3). Furthermore, the differentiated trusting rates (the difference of TRs between chatbot and human services) for the subjective task ($M = 0.171$, $SE = 0.038$) were larger than those of the objective task ($M = 0.035$, $SE = 0.013$, $t\,(34) = -3.945$, $p = 0.000$).

The behavioral results in the ERP study explored the differences of consumer trust in chatbot service and human service in the coping process of CAT. And the results showed that consumers had a higher trusting rate in chatbot (vs. human) service interaction, which was consistent with what was found in the pilot behavioral study. When the results of consumer trust in the pilot study and the ERP study are considered together, H2 is supported. Moreover, another finding was that there was a moderating effect of task type on consumer trust in

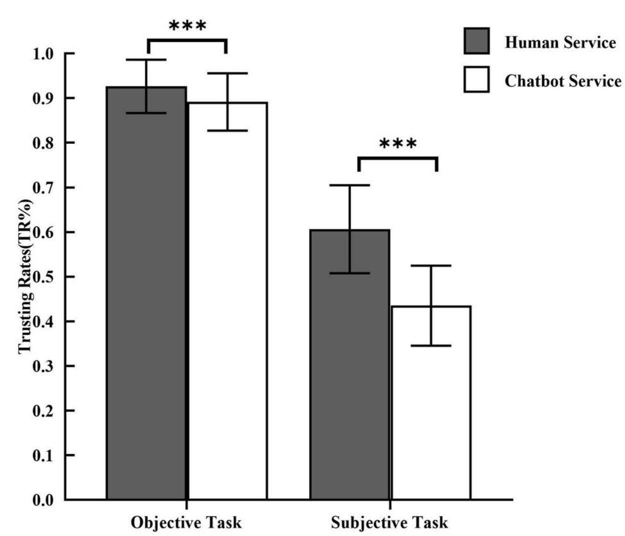

Fig. 3. Mean trusting rates (TRs) to human service and chatbot service were sorted by task type in the ERP study. Error bars indicate the SE of the TRs. ***$p < 0.001$.

chatbot/human service. Thus, H4 is supported.

4.4. Discussion

Besides the pilot study to investigate emotional experience and trust at the behavioral level, the ERP experiment was conducted to reveal the brain activities when consumers interacted with chatbot or human services in e-commerce. The ERP components of P2 and LPP were examined to reflect the appraisal process of emotional experience in CAT, providing neural evidence for understanding the process of consumer interaction with chatbot/human services.

The ERP study found that the chatbot (vs. human) service elicited a larger P2 amplitude at the subconscious processing stage. P2 as an attention-related component can be enlarged by negative emotional stimuli than positive or neutral emotional stimuli, reflecting a more significant automatic mobilization of attention resources for negative emotional stimuli (Paulmann et al., 2013; Yang et al., 2012; Lu et al., 2017). Thus, the results of P2 indicated that chatbot service as a negative emotional stimulus can automatically attract more attention resources than human service in the emotional experience appraisal process. Meanwhile, a larger LPP was elicited by chatbot (vs. human) service at the conscious processing stage. LPP is a temporally functional indicator of emotion regulation and reflects the engagement of controlled cognitive resources related to emotional processing in the regulation effect (Gardener et al., 2013; MacLeod et al., 2017; Chung et al., 2020). Thus, the results of LPP show that consumers purposively distributed more cognitive resources to regulate the negative emotions elicited by chatbot (vs. human) service. Combined with the results of P2 and LPP, the appraisal process of consumers' emotional experience in CAT can be better understood.

Moreover, the moderating effect of task type happened during the conscious process rather than the subconscious stage, which was reflected by the LPP component instead of the P2 component. Consumers believe that chatbots lack the emotional ability to perform subjective tasks, and they resist chatbots more for the subjective than the objective tasks (Inbar et al., 2010; Castelo et al., 2019). Therefore, the moderating effect of task type on LPP showed that chatbots attracted more cognitive resources for negative emotion regulation than human services when consumers interacted for the subjective task. In addition, Trope and Liberman (2003) demonstrated that the same object can be processed at different levels, ranging from low-level to high-level representations. Consumers automatically processed the information of the service category first at the subconscious stage and without distributing resources to process the information of task type. The effect of task type information was consciously processed at the conscious stage.

Behaviorally, consumers more trust the consequences of human (vs. chatbot) services and the solutions of objective (vs. subjective) tasks. Moreover, t trusting rates between chatbots and humans were much more different in the subjective tasks than in the objective tasks. These results are consistent with previous studies that negative attitude is related to AI service rather than human service, and task type affects consumers' trust attitude toward AI service (Castelo et al., 2019; Yun et al., 2021; Garvey et al., 2022). In addition, combining the results of the pilot study, different emotional experiences led to different trust attitudes, which verified the applicability of CAT to chatbot/human service interaction.

5. Implications

This study entails a profound investigation to explore the differences of consumer trust between chatbot and human services from the perspective of interacting emotional experiences using the ERP method, while taking into account the moderating effect of task type (objective vs. subjective). Building on CAT, we identified the appraisal and coping processes associated with chatbot/human service interaction and explored the underlying neurocognitive mechanisms of the emotional experience appraisal process. A pilot behavioral study and an ERP study were conducted in the current study. The main findings showed that the negative emotional experience evoked by chatbot service interaction can be understood using neural data from attention attraction in the subconscious process to emotion regulation in the conscious process. Moreover, the findings that consumers trust chatbots less were further verified in the ERP study. In addition, relative to objective tasks, we found larger differences between chatbot service interaction and human service interaction for the subjective tasks, which were reflected by LPP and trust ratings.

5.1. Theoretical implications

This study provides important theoretical insights. First, we expand the understanding of the differences between chatbot and human services from the implicit perspective of the interaction process in e-commerce. Most previous studies on consumer attitudes toward chatbot/human services were from the perspective of explicit information processing (Longoni et al., 2019; Cadario et al., 2021). This study used cognitive appraisal theory to explain the implicit differences of emotional experience when consumers passively interacted with chatbot/human services in e-commerce. Moreover, we thoroughly explored the modulating effect of task type on chatbot/human service interaction using neural data. At the neural level, the moderating effect of task type on emotional experience was only observed in the subconscious process, but with no moderating effect in the subconscious process. These neural findings can help further understand the influences of task type on how consumers evaluate chatbots.

Second, we identify the unconscious and conscious appraisal process in CAT with neuroscience evidence. The CAT model includes two cognitive stages: appraisal and coping (Ying et al., 2021). The appraisal process for emotional experience is a complex and conceptualized cognitive process in which a person's esthesis results in beneficial or harmful responses to the stimuli of the environment and events (Lazarus, 1991; Ying et al., 2021). The explicit differences of interaction experiences between chatbot and human services can be reflected by CAT, which verifies the causality between emotional experience appraisal and trust response toward chatbot/human services. More importantly, the implicit appraisal process of the chatbot/human service interaction can be further demonstrated from subconscious attention bias to the conscious emotion regulation processes by ERP components, which adds direct neural evidence to represent the appraisal process in CAT.

Third, we contribute to the discourse on consumer neuroscience by linking the service experience evaluation process with chatbot/human services and task type. Previous ERP studies have highlighted the role of visual modality (text or face) in AI (vs. human) agents and suggested that consumers perceive higher unnaturalness toward AI (Chung et al., 2020). Our study focuses on the emotional experience when consumers interact with chatbot/human services and employs ERP components to reflect the emotional experience appraisal process and investigate the underlying neural mechanism. According to current findings, consumers appear to have a negative emotional experience with chatbots rather than humans when interacting. Our experiment results in a novel approach to studying consumer experience and attitude in neuromarketing.

5.2. Practical implications

The current study also has important practical significance for improving online customer service with chatbot/human services in e-commerce. First, we found that consumers had more negative emotional experiences when interacting with chatbot (vs. human) service, which led to less trust in chatbot service, though no difference existed between the solutions of chatbot and human services. For a chatbot designer or provider, eliminating negative consumer emotions toward chatbots is more important (at least as necessary) than improving algorithm accuracy. For example, chatbot providers can design some empathic gambits to establish a positive relationship to help alleviate negative emotions (Lv et al., 2022). Meanwhile, chatbot providers should strengthen their efforts to publicize the benefits of chatbots to change consumers' mindsets in the long run. Before deploying chatbots, e-commerce enterprises should recognize that chatbot services are not capable of completely replacing humans at the current stage, and they should weigh lower usage costs against lower consumer trust.

Second, the current findings demonstrate that consumers have a less negative emotional experience when interacting with chatbots for objective (vs. subjective) tasks. Thus, e-commerce enterprises must consider the objective characteristic of tasks before deploying chatbots for customer service. Consumers are more concerned about the attribute information of search products and the experience information of experience products (Luan et al., 2016). We can speculate that consumers would ask more objective questions before purchasing a search product (i.e., cell phone), Likewise, they would ask more subjective questions before buying an experience product (i.e., clothing). Hence, e-retailers should deploy chatbots for search products and adopt continuous employment of human or human-AI cooperation for experience products in e-commerce.

5.3. Limitations and future research

This study has several limitations that must be addressed. First, we only studied chatbots in the context of online customer service, and the findings may not be universally applicable to other contexts of chatbot engagement. Past research has identified that AI prioritizes the agency domain of employee selection, hiring decisions, or task assignment (Diab et al., 2011; Longoni and Cian, 2022; Bai et al., 2020). Future research on AI interaction can expand from serving front-line consumers to engaging staff in enterprises. Second, we explored consumers' emotional experience in the interaction with chatbots, but did not extend to detecting post-service experience, especially in service failure scenarios. Some recent studies have demonstrated that chatbot service failure impacts customers' tolerance emotions (Lv et al., 2021). Future research can explore the different effects of the experience encountered after chatbot service, even after chatbot service failures. Third, the experiment of this study utilized high temporal resolution neural measurement tools (ERP) to measure interaction processes with chatbot/human services, but the spatial resolution of ERP is not significant (Luck, 2014). Emotions from consumer experience are detected in the right amygdala of the brain (Heutink et al., 2011). Neural diversity tools with incredibly high spatial resolution technology (i.e., fMRI) should be used in future studies. In addition, all the recruited participants in our ERP study were college students. Further research can consider subjects with more varied backgrounds to enhance the robustness and generalizability of our conclusions.

CRediT authorship contribution statement

CW, YL, WF and JJ conceived and designed the two experiments. YL, JJ and CW performed the ERP experiment. YL, WF and CW performed the behavioral experiment. YL, CW and JJ analyzed the data. CW, YL, WF and JJ wrote and refined the article. All authors contributed to the article and approved the submitted version.

Ethics approval and informed consent

The procedures of this study were reviewed and approved by the Laboratory of Brain and Cognitive Behavioral Neuroscience of Shanghai International Studies University. Written informed consent was obtained from each participant. All data collected from the subjects were kept anonymous and confidential to protect the privacy of the study subjects.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Data availability

Data will be made available on request.

Acknowledgments

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jretconser.2023.103325.

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