Article:

Wu, S., Peng, G., Li, S. et al. (2026) Textual cues, cognitive load, and social fatigue: Unveiling the reasons behind user discontinuance in conversational AI. International Journal of Human-Computer Studies. 103846. ISSN: 1071-5819

https://doi.org/10.1016/j.ijhcs.2026.103846

Highlights

Textual Cues, Cognitive Load, and Social Fatigue: Unveiling the Reasons Behind User Discontinuance in Conversational AI

Siyuan Wu, Guochao Peng, Shuyang Li, David Cameron, Jun Zhang, Justin Zhang, Qing Zhang

- Textual cues, including dialog length and information volume, play a crucial role in influencing users' discontinuance of conversational AI.
- Users' cognitive load and social fatigue sequentially mediate the influence of textual cues on discontinuance in conversational AI.
- The development of discontinuance in conversational AI can be attributed to a variety of obstacles, including technological obstacles, interaction obstacles, readability obstacles, experiential obstacles, and psychological obstacles.
- Technological, interaction, and readability obstacles collectively impact consumers' discontinuance by influencing both experiential and psychological obstacles.

Textual Cues, Cognitive Load, and Social Fatigue: Unveiling the Reasons Behind User Discontinuance in Conversational AI⋆

Siyuan Wu[a,b], Guochao Peng[b,*], Shuyang Li[c], David Cameron[d], Jun Zhang[d], Justin Zhang[e] and Qing Zhang[b]

[a] *Sun Yat-sen Library of Guangdong Province, Guangzhou, China*
[b] *School of Information Management, Sun Yat-sen University, Guangzhou, China*
[c] *Birmingham Business School,University of Birmingham, Birmingham, UK*
[d] *School of Information, Journalism and Media, The University of Sheffield, Sheffield, UK*
[e] *Department of Management, Coggin College of Business, University of North Florida, Florida, USA*

ARTICLE INFO

Keywords:
Textual cues
Cognitive load
Social fatigue
Discontinuance
Conversational AI

ABSTRACT

Conversational AI is transforming organizational practices across various sectors, significantly reshaping marketing strategies and consumer behaviors. To ensure the continuous use and sustainable development of conversational AI, it is essential to understand the reasons behind users' discontinuation. This study employs a sequential two-stage mixed-methods approach to explore the drivers of users' discontinuance in relation to conversational AI. A 2 (dialog Length: long vs. short) x 2 (information volume: high vs. low) between-subjects experimental design is utilized to identify the actual role of the textual cues of conversational AI on users' discontinuance intentions. Subsequently, a qualitative study is conducted to examine the obstacles and challenges that affect users' ongoing engagement with conversational AI from the perspective of the customers themselves. The quantitative findings reveal that long dialog and high information in conversational AI, fully mediated by users' cognitive load and social fatigue, lead to higher discontinuance intentions. The qualitative results further illuminate a set of obstacles and inter-relationships between obstacles that users undergo when discontinuing the use of conversational AI. These findings offer new insights into consumers' discontinuous usage of conversational AI while also providing practical implications for e-commerce companies and technology providers to implement and improve conversational AI strategies.

1. Introduction

Conversational AI based on text generation has played a vital role in communication between service organizations and customers in recent years (Sachdeva et al., 2024; Hsu and Lin, 2023; Huang et al., 2021), particularly within online retail and e-commerce platforms (Munnukka et al., 2022; Chandra et al., 2022; Hsu and Lin, 2023). Many companies are leveraging conversational AI to enhance customer service and communication (Hsu and Lin, 2023), with the aim of addressing service failures such as product returns and customer complaints (Huang et al., 2021; Rai, 2020) and rebuilding trust (Toader et al., 2019). Big tech companies such as Google and Amazon have widely acknowledged the transformative potential of conversational AI to improve user engagement, reduce labor costs, and elevate overall operational efficiency (Chandra et al., 2022). Conversational AI is therefore considered an effective digital solution that is transforming both marketing strategies and consumer behaviors (Davenport et al., 2020; Hsu and Lin, 2023; Dwivedi et al., 2023).

However, a critical challenge persists: user discontinuance, in which customers may deliberately avoid or abstain from using conversational AI. This trend is particularly evident in service failures and product return contexts, where user satisfaction remains low and discontinuance frequently occurs (Grimes et al., 2021; Castillo et al., 2021; Hsu and Lin, 2023; Zhou and Chang, 2024). This discontinuance of conversational AI by customers may lead to potentially serious consequences, including customer dissatisfaction with products and services, negative reputations of products and companies, online innovation failures, and increased labor costs (Heidenreich and Handrich, 2015; Crisafulli and Singh, 2017; Honora et al., 2022; Zhou and Chang, 2024). Despite the significant consequences of user discontinuance, research on the discontinuance of conversational AI has been underexplored, especially understanding how language design in conversational AI shapes user perceptions and trigger discontinuance. Therefore, it is necessary to examine the factors contributing to users' discontinuance of conversational AI to help service providers improve retention, sustain usage intention, and ensure the long-term success of this AI innovation.

Information systems (IS) discontinuance is a persistent concern that has been recognized for nearly three decades (Soliman and Tuunainen, 2022). Previous studies have identified various discontinuance antecedents, including factors outside the individual—such as technology breakdowns, difficulty in interacting, and information irrelevance (Cenfetelli and Schwarz, 2011; Colace et al., 2017; Zamani and Pouloudi, 2021)— and individual factors such as discomfort, fatigue, distrust, and dissatisfaction (Zhang et al., 2016; Cao

*Corresponding author
**Principal corresponding author
wusy28@mail2.sysu.edu.cn (S. Wu); penggch@mail.sysu.edu.cn (G. Peng); shuyang.li@sheffield.ac.uk (S. Li); d.s.cameron@sheffield.ac.uk (D. Cameron); j.zhang3@sheffield.ac.uk (J. Zhang); zhangq659@mail.sysu.edu.cn (Q. Zhang)
ORCID(s): 0000-0003-1053-5693 (S. Wu)

and Sun, 2018; Luo et al., 2019; Munnukka et al., 2022). However, the role of language design—specifically textual cues in AI-generated responses, such as dialog length and information volume—in conversational AI remains underexplored. Earlier research in online communication has examined users' impressions and attitudes in interactive textual conversations and found that textual cues can significantly shape users' perceptions and assessments of a communicator(Hancock and Dunham, 2001; Davis et al., 2001; Araujo, 2018; Schuetzler et al., 2020). Thus, the neglect of textual cues in conversational AI may have an adverse influence on user engagement and adoption. Furthermore, in the context of conversational AI, where discontinuance is better understood as a process rather than a static construct (Soliman and Tuunainen, 2022), the relationship between user psychology, cognition, and discontinuance of conversational AI remains largely unexplored. It is thus important to investigate how textual cues in conversational AI can influence users' discontinuance from a psychological and cognition science perspective.

To comprehensively understand users' discontinuance of conversational AI, this study adopts a sequential mixed-methods approach guided by the Stimulus-Organism-Response (S-O-R) framework (Jacoby, 2002). While prior research has primarily focused on isolated factors (e.g., technical failures or user fatigue), we argue that discontinuance is a multilayered phenomenon, driven by direct stimuli (e.g., textual cues) and internal psychological states (e.g., cognitive load and social fatigue), and influenced by contextual obstacles (e.g., technological, interactional, or readability obstacles). To capture this complexity, we propose two interlinked research questions:

1) How do textual cues of conversational AI (as stimuli) directly shape users' discontinuance?

2) How do other stimuli factors interact with textual cues to amplify users' discontinuance intentions through cognitive and psychological states (organism)?

These two questions are closely interlinked: the first establishes the foundational understanding of how textual cues directly influence users' discontinuance, mediated by cognitive load and social fatigue, while the second builds on this foundation by examining how textual cues interact with broader stimuli factors (e.g., technological, interaction, and readability obstacles) in real-world settings. This sequential design ensures that the two research questions progressively reveal the mechanisms of discontinuance—from isolated stimuli to holistic user experiences.

To address these questions, we employed a sequential mixed-methods design combining quantitative and qualitative analyses. First, we conducted a quantitative experiment to investigate the direct impact of conversational AI's textual cues on users' discontinuance, focusing on the mediating roles of cognitive load and social fatigue. Subsequently, we designed a qualitative study to explore real-world obstacles from the perspective of customers themselves, extending and complementing the findings of the quantitative study. This approach not only validates the direct effects of textual cues but also uncovers how these cues interact with broader contextual obstacles—a critical yet overlooked aspect in prior research.

Our study makes three key contributions to the literature. First, it highlights the role of stimuli (textual cues) and organisms (cognitive load and social fatigue) in users' discontinuance of conversational AI. Second, it contributes to the literature by revealing not only five categories of obstacles that contribute to users' discontinuance of conversational AI but also the interrelationships among these obstacles from the S-O-R perspective. Finally, the findings elucidate the mechanisms of discontinuance and offer actionable insights to improve conversational AI, which should be of significant interest to researchers, AI manufacturers, and e-commerce companies.

2. Literature review

2.1. Conversational AI and user discontinuance

Conversational AI can be defined as a disembodied virtual assistant that engages in text-based communication with users using natural language processing and deep learning(Araujo, 2018; Ciechanowski et al., 2019; Ashfaq et al., 2020)—an emerging technology with significant business potential(Luo et al., 2019). The substantial convenience and economic benefits provided by conversational AI have resulted in its widespread adoption in customer service operations for online retail businesses and e-commerce platforms (Wedel and Kannan, 2016; Przegalinska et al., 2019; Munnukka et al., 2022).

Research into conversational AI has gained considerable attention across multiple disciplines in recent years. Marketing researchers focus on consumers' perceived service quality (Chen et al., 2023), loyalty (Hsu and Lin, 2023), and stickiness (Chen et al., 2023; Hsu and Lin, 2023), as well as employees' diverse utilization patterns of conversational AI (Gkinko and Elbanna, 2023), from the perspective of the firm and customers. In addition, researchers in information systems and behavioral science have focused on several clusters, such as user satisfaction (Chen et al., 2021), adoption (Laumer et al., 2019; Pillai and Sivathanu, 2020), acceptance (Brachten et al., 2021; Zhu et al., 2022), continuance intention (Ashfaq et al., 2020) , trust, and distrust (Rese et al., 2020; Jiang et al., 2023). However, these studies have not fully addressed the limited acceptance of conversational AI among online shopping users (Nguyen et al., 2019; Ashfaq et al., 2020; Luo et al., 2019), or the phenomenon of customers deliberately avoiding or opposing its use. The study of users' discontinuance of conversational AI has received little attention from service scholars.

Discontinuance refers to the cessation of information systems usage that occurs when technology falls short of user expectations (Li et al., 2011; Furneaux and Wade, 2011). It could happen at both organizational level and the individual level, manifesting in various forms including quitting, temporary discontinuance, regressive discontinuance, rejection, and replacement (Soliman and Rinta-Kahila,

Table 1
Summary of studies about discontinuance of conversational AI.

		References
Topics Studied	Reducing discontinuance after response failures; Frontline chatbot service failures; Inhibitors and enablers in technology usage; Technostress	Weiler et al. (2022); Chen et al. (2024); Khan et al. (2024); Furneaux and Wade (2011); Li et al. (2011); Cao and Sun (2018); Cenfetelli (2004); Cenfetelli and Schwarz (2011); Ravindran et al. (2014); Zamani and Pouloudi (2021); Zhang et al. (2016); Zhang and Tong (2024)
Context Investigated	Sales; Mental health; Blogsphere; Social media; SNS; ChatGPT	
Methods used	Experiment; Surveys; mix-method of interviews and experiments; mix-method of interviews and survey; surveys with time sequence; qualitative social media data analyzed by Grounded Theory method	
Main variables and findings relevant to discontinuance	Inhibitors and enablers; Satisfaction and fit; System capability (e.g. chatbot efficiency and performance); Technostress and anxiety; Workarounds and reframing; Fatigue	

2020; Zamani and Pouloudi, 2021). IS discontinuance poses a significant challenge for digital technologies today. Despite being a widespread concern, it has garnered considerably less attention compared with extensive research on adoption, acceptance, and continuance (Soliman and Rinta-Kahila, 2020; Cao and Sun, 2018).

Research in the information systems and marketing literature has verified that discontinuance may occur due to various factors, including technological issues such as breakdowns (Zamani and Pouloudi, 2021) and intrusiveness (Cenfetelli, 2004), information-related factors such as information irrelevance (Cenfetelli and Schwarz, 2011), and user psychological factors such as overload (Cao and Sun, 2018), social fatigue (Ravindran et al., 2014) and dissatisfaction (Zhang et al., 2016). In particular, social fatigue has been identified as a significant factor driving the intention and behavior associated with discontinuance (Ravindran et al., 2014; Yao and Cao, 2017; Zhang et al., 2016). Yao and Cao (2017) founded that stress induced by users' social networking services could result in behavioral responses such as temporary cessation, decreased usage frequency, and termination. Zhang and Tong (2024) focused on ChatGPT found that perceived AI characteristics, AI anxiety, and user negative attitudes can positively influence their discontinuous usage of AI systems. A summary of studies focusing on the discontinuance of conversational AI is presented in Table 1. These findings offer a theoretical basis and inspiration for exploring the interruption behavior of conversational AI users.

2.2. Social Fatigue

Social fatigue, originally conceptualized in the context of social media use, refers to the psychological exhaustion resulting from prolonged or intense social interactions (Zhang et al., 2016; Ravindran et al., 2014). While conversational AI differs from social media, social fatigue still exists in human-AI interactions. Conversational AI is designed to create a social presence that makes users feel as though they are interacting with socially aware and intelligent entities. However, this seamless human-AI interaction may also trigger social fatigue, as users may experience cognitive load from lengthy replies or repetitive interactions, leading to frustration and exhaustion (Shi and Xu, 2024; Divya et al., 2018; Zhang and Tong, 2024). Rudroff (2024) highlighted that conversational AI, such as ChatGPT, enables smooth interactions between humans and AI and has the potential to advance research on human fatigue.

Social fatigue has been recognized as a significant social response to human-computer interactions (Rudroff, 2024; Shi and Xu, 2024; Divya et al., 2018). Forced, addictive, or excessive use of conversational AI can lead to feelings of lead to burnout and exhaustion (Yankouskaya et al., 2025; Sun et al., 2022). Researchers have also found that users' perception of cognitive load can significantly contribute to social fatigue (Cao and Sun, 2018; Chen et al., 2019). For instance, Zhang et al. (2016) discovered that users' cognitive load can influence social network fatigue, thereby potentially triggering their discontinuance. In addition, social fatigue in conversational AI can diminish users' willingness to continue interactions, leading to discontinuance behaviors such as reduced usage frequency, social avoidance (Duong et al., 2024), or complete abandonment (Ravindran et al., 2014; Zhang et al., 2016). These findings highlight the importance of considering social fatigue as a critical factor in understanding users' discontinuance of conversational AI interactions.

2.3. Textual cues

Conversational AI primarily uses conversational cues (e.g., emoticons, textual cues, contextualization cues, photographic cues) to engage with users and convey information (Araujo, 2018; Feine et al., 2019; Huang et al., 2021). As with face-to-face communication, textual cues are a defining feature of interactions in online communication (Huang et al., 2021; Kang et al., 2021). Evidence suggests that textual cues influence users' perceptions and judgments about the communicator (Hancock and Dunham, 2001). Davis et al. (2001) demonstrated that consumers tend to avoid reading or studying texts they perceive as too difficult. However, it remains unclear how textual cues of conversational AI affect users' sensuousness toward information processing and their intention to avoid conversational AI.

Previous research has examined several textual cues that influence users' perceived difficulty of a text, including the vocabulary used, grammatical structures, information density, and text length (Hancock and Dunham, 2001; Munnukka et al., 2022; Leroy et al., 2010). For example, some researchers use word length or text length as proxies for semantic and syntactic complexity or difficulty when determining text readability using formulas (Flesch, 1948; Dubay, 2004; Leroy et al., 2010). Previous research has also demonstrated a significant correlation between information density, word frequency, and textual readability (Crossley et al., 2008; Chen and Meurers, 2018). In general, longer texts and high information density tend to increase reading difficulty and response times of readers (Nattkemper and Prinz, 1990; Ziefle et al., 2005). However, the impact of dialogue length and information density on outcomes beyond the lexical and text levels has not yet been fully elucidated (Genzel and Charniak, 2002; Jaeger, 2010). Especially among service chatbots, there has been limited scholarly exploration of how dialog length and information density of conversational AI in online communications affect customers' cognitive psychology and behavioral intentions. Considering the significance of textual cues—such as dialog length and information density—and the need to broaden the predominant but restricted research focus of previous studies, this study aims to explore whether cognitive psychology, such as cognitive load and social network fatigue, fully or partially mediates the relationship between conversational AI's textual cues and users' discontinuance.

Information is defined theoretically in terms of probabilities (Shannon, 1948). Researchers commonly use Shannon's information entropy to measure information density (Golan, 2002; Jaeger, 2010). In this article, the information provided by the AI fundamentally comprises substantive nouns and verbs bearing concrete semantic content, and therefore we defined information volume as the amount and density of nouns and verbs conveyed in conversational AI. Building upon the Shannon information formula, we calculate the probability of occurrence of individual nouns within this conversational interactions. The aggregate information volume is derived from the summation of Shannon entropy values across all identified nouns, while lexical count metrics serve as the operational proxy for utterance length in dialog texts.

3. Hypotheses development

3.1. The effects of textual cues

Textual cues in AI are employed to achieve realistic human-like conversational behavior (Cassell, 2001). They play a crucial role in facilitating experiential communication by capturing and retaining customer attention and effectively addressing user queries (Moffett et al., 2021). Textual cues signaled by conversational AI, especially in the retail service industry (e.g., Amazon and AliExpress), are important indicators of online service quality. Prior studies have indicated that users could exhibit different social responses depending on the features of textual cues (Ghazali et al., 2018; Brandtzaeg and Følstad, 2018; Go and Sundar, 2019). Dialog length and information density are identified as the two most critical features of textual cues that can determine information delivery and conversation effectiveness (Bailin and Grafstein, 2001; Friedman and Hoffman-Goetz, 2006). These features can influence the perceptions and judgments of users towards the communicator (Hancock and Dunham, 2001; Feine et al., 2019), leading to either continued engagement with or avoidance of the conversation.

As suggested by Munnukka et al. (2022), shorter dialog facilitated by conversational AI can enhance consumer satisfaction. In contrast, longer conversations or reviews can cause users to devote more attention to them, leading to information overload and higher information processing costs (Fink et al., 2018). Moreover, higher information density or volume can also impact users' discontinuance intention. Studies also have shown that texts readability is influenced by information density, with high-density texts being more difficult to understand than low-density texts (Leroy et al., 2010). Studies further suggest that in conversational AI contexts, high information density increases the likelihood of providing users with irrelevant information, which can directly contribute to social fatigue (Guo et al., 2020) and ultimately lead to discontinuance (Zhang et al., 2016). For instance, when users ask to reset passwords but receive AI responses packed with troubleshooting, security, and policy information, the high-volume information generates excessive cognitive load that increases the likelihood of users' discontinuance. Therefore, this study posits that long dialog and higher information density can impact users' discontinuance intention. Accordingly, we hypothesize:

H1a: Users will have higher discontinuance intentions for a chatbot using textual cues of long (vs. short) dialog.

H1b: Users will have higher discontinuance intentions for a chatbot using textual cues of high-volume (vs. low-volume) information.

3.2. The mediating role of cognitive load

Cognitive load, a critical mental activity, refers to the amount of mental effort exerted by working memory while performing a cognitive task and interacting with a system (Zagermann et al., 2016). Information processing theory posits that an abundance of information can increase the mental effort required of individuals, potentially restricting the usage of that information (Schroder et al., 1967). Cognitive load theory suggests that an increase in the amount of information leads to a higher cognitive load during reading (Wong et al., 2012), which may deter continuous reading or system use.

Additionally, longer texts tend to attract more attention because they occupy more screen space and contain more information (Tversky and Kahneman, 1974; Kuan et al., 2015). Thus, textual cues such as dialog length and information volume significantly influence users' cognitive load. For example, when a user asks a conversational AI for a recipe and receives a long, meandering response, the user must simultaneously filter irrelevant details, hold key steps in memory, and organize the information sequence. This high-effort processing of a lengthy and dense dialog directly increases cognitive load.

Numerous studies have documented the negative effects of increased cognitive load on behavior and decision-making across various contexts (Driver and Mock, 1975; Jones et al., 2004; Fink et al., 2018). In light of this evidence, we hypothesize:

H2a: Users' cognitive load will mediate the impact of dialog length on users' discontinuance intentions.

H2b: Users' cognitive load will mediate the impact of information volume on users' discontinuance intentions.

3.3. The mediating role of social fatigue

Fatigue is subjectively experienced as an unpleasant feeling—an unconscious negative emotional response to stressful situations. In the field of Human-Computer Interaction (HCI), this reaction can manifest as tiredness, boredom, burnout, indifference, and diminished interest when using technology (Maier et al., 2015a). Considering that both the content and stylistic elements of messages trigger social reactions (Walther, 2006), textual cues similarly affect users' social fatigue. For instance, when a user interacts with a conversational AI that delivers information in long, monotonous, and socially inept paragraphs—lacking the natural brevity of human talk—the interaction may feel like a tiresome monologue, thereby inducing social fatigue.

Among users experiencing stress and fatigue, discontinuous intention often emerges. This intention stems from users' desire to mitigate the adverse effects of technology and information overload and to maintain emotional stability. Consequently, when users are overwhelmed by the dense content on social media platforms, passive usage behaviors, including ignoring, resisting, avoiding, transferring, and ultimately withdrawing, become widespread (Bright et al., 2015). Accordingly, we hypothesize:

H3a: Users' social fatigue will mediate the impact of dialog length on users' discontinuance intentions.

H3b: Users' social fatigue will mediate the impact of information volume on users' discontinuance intentions.

3.4. Serial mediation

Longer texts or higher information density can increase cognitive load for the reader (Zhang et al., 2024), resulting in physical and psychological fatigue, which often prompts individuals to escape (Lee et al., 2016). Numerous studies have explored the link between cognitive load and social fatigue (Ravindran et al., 2014; Zhang et al., 2016; Yao and Cao, 2017), and social fatigue is commonly viewed as a consequence of this overload (Guo et al., 2020). Specifically, social fatigue has been identified as a form of psychological strain caused by overload (Maier et al., 2015b; Cao and Sun, 2018). For example, when a user is faced with a conversational AI that provides a high-density, lengthy explanation of a return policy, the mental effort required to decipher the terms (cognitive load) can gradually evolve into a feeling of being socially drained by the interaction (social fatigue).

In addition, Ravindran et al. (2014) indicates that social fatigue is a critical factor in discontinuance. Furthermore, empirical research by Zhang et al. (2016) has confirmed that perceived overload in social networks leads to fatigue, and that both factors significantly increase the likelihood of users discontinuing their use. Given these findings, we view cognitive load and social fatigue as typical psychological responses arising from textual cues in conversational AI, which in turn influence users' discontinuance.

H4a: Users' cognitive load and social fatigue will sequentially mediate the impact of dialog length on users' discontinuance intention.

H4b: Users' cognitive load and social fatigue will sequentially mediate the impact of information volume on users' discontinuance intention.

The hypothesized relationships are depicted in the conceptual model, as illustrated in Fig.1.

4. Methodology

4.1. Mixed-method

The main aim of this paper is to explore the complexity of the antecedents influencing users' discontinuance of conversational AI. Specifically, we seek to uncover comprehensive and detailed insights into how technological, interactional, readability, and other barriers impact users' discontinuance intentions toward conversational AI.

To address this aim, we have designed a comprehensive research methodology (Ivankova, 2014; Creswell and Creswell, 2017): quantitative study and qualitative study. Our research is conducted in two interrelated stages that together address both the "how" and the "why" behind users' discontinuance of conversational AI. The quantitative phase explains how textual cues in conversational AI shape users' discontinuance, while the qualitative phase delves into why specific antecedents lead to discontinuance by exploring the underlying obstacles. Therefore, it is appropriate to adopt the mixed-method approach using a sequential design (QUAN→QUAL) in our research (Teddlie and Tashakkori, 2003; Venkatesh et al., 2013).

Quantitative study: we conducted an experiment to answer our confirmatory research questions. Experiments are usually considered the best way to identify causal relationships (Haas and Kraft, 1984; Crossler et al., 2013). Our experimental study verified the process or path through which textual cues influence users' discontinuance via cognitive load and social fatigue. Therefore, it is appropriate to use an experimental design in the first stage of this study to address our first research question.

Qualitative phase: we conducted semi-structured interviews to explore our research questions in greater depth.

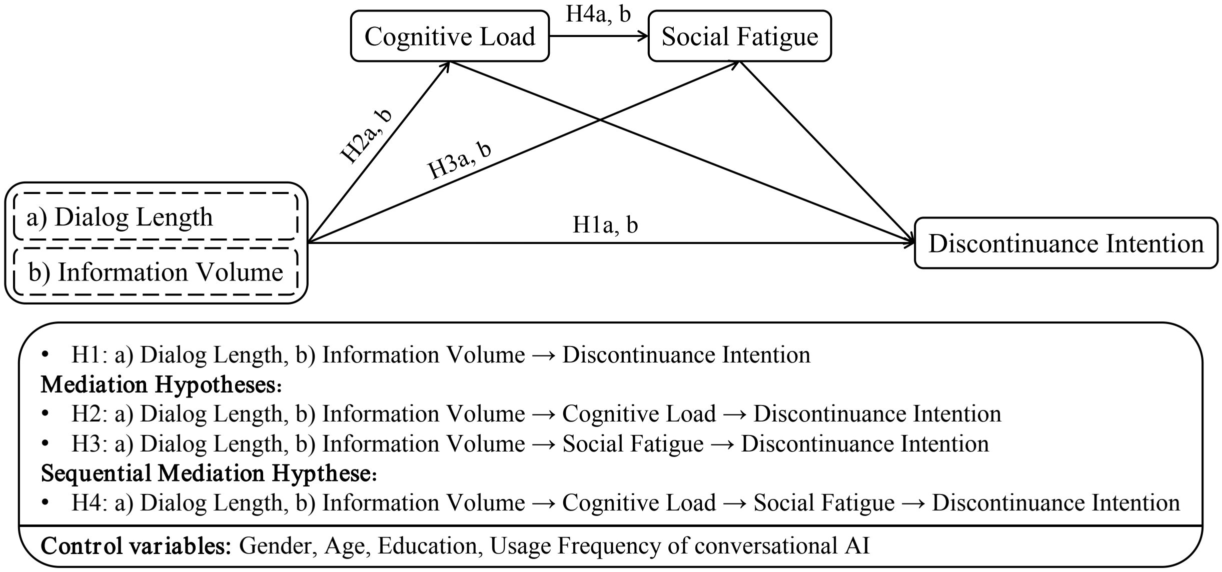


Figure 1: The theoretical base model for this study.

The findings from the quantitative phase provided a foundation for developing the interview guide and helped us to formulate specific research sub-questions. Through in-depth interviews, we aimed to identify additional antecedents and explain why those factors drive users' discontinuance of conversational AI. The qualitative insights gained in this stage not only corroborate but also enrich the findings from the first stage, offering a more comprehensive understanding of the phenomena under study.

4.2. Experiment

4.2.1. Experiment setting and Stimuli

We employed a 2 (dialog length: long vs. short) x 2 (information volume: high vs. low) between-participant experimental design, which resulted in a total of four treatment groups and the development of four different conversational AI prototypes. The randomization process of experiments can yield unbiased estimates of the average treatment effect (Cook et al., 2002; Steiner et al., 2010). Therefore, participants in the quantitative study were randomly assigned to one of the four conversational AI behavior experiments to avoid selection bias.

Given that the experiment aimed to simulate a "Question and Answer" format in online conversational AI interactions, we utilized chat simulations resembling an instant messaging interface. Our experimental scenario was developed based on prior research (Smith et al., 1999).To manipulate dialog length and information volume in conversational AI, we prepared the corpus of questions and developed textual responses for four distinct corpora, each corresponding to a different chatbot.

Table 2
Factorial design.

		Information Volume	
		High	Low
Dialog Length	Long	A (2004 words, 7.3 bit)	C (1822 words, 6.8 bit)
	Short	B (1212 words, 7.1 bit)	D (493 words, 6.1 bit)

Due to information entropy serving as an effective measure of information volume (Shannon, 1948), we used the information entropy of nouns and verbs bearing concrete semantic content to control and measure information volume in the textual cues of a chatbot. The information volume of reply text for each type of conversational AI is calculated as follows:

$$H(\text{relpy text}) = -\sum_{j=1} \frac{f_{ij}}{\sum_{k\in j} f_{kj}} \log_2 \frac{f_{ij}}{\sum_{k\in j} f_{kj}}$$

Where f_{ij} is the count of nouns or verbs with specific semantic content in reply text j, $\sum_{k\in j} f_{kj}$ is the total count of all nouns or verbs with specific semantic content in reply text j. We also used word count to control and measure dialog length in the textual cues of a chatbot. Therefore, we controlled and measured dialog length and information volume, as shown in Table 2 below. All four conversational AI prototypes produced the same result to prevent confounding and biases (presented in Appendix A).

Table 3
Sample distribution of the experiment.

AI Prototype	Dialog Length	Information Volume	Number	Proportion
A	Long	High	36	25.4%
B	Short	High	36	25.4%
C	Long	Low	35	24.6%
D	Short	Low	35	24.6%

4.2.2. Samples

We conducted the experiment in a laboratory setting, targeting consumers who shop online. We posted notices about the recruitment experiment on social media and then invited participants to enter Sun Yat-sen University for the offline experiment. We assured all participants of complete anonymity and confidentiality throughout the experiment, emphasizing that the collected data would be utilized exclusively for academic research purposes. Furthermore, we clarified that there were no right or wrong answers to any questions posed. These instructions enabled participants to respond to questions candidly and without reservation.

Finally, a total of 150 respondents participated in our experiment. Of these, eight were excluded: two who guessed the purpose of the experiment, two who had no prior experience interacting with an online chatbot, and four who provided incorrect answers to attention-check questions. A total of 142 (effective rate 95%) participants were included in this study and table 3 presents the distribution of participants in each group in the experiment. According to a power analysis software G*Power3.1.9.7 (Faul et al., 2007), our sample size (n = 142) was larger than the estimated sample size (n = 84) required to detect the effect size of 0.4 with β error rate of 0.05. Hence, our sample size of 142 provided adequate statistical power.

Table 4 presents on overview of demographic characteristics in the experiment. Female respondents constituted 56.3% of the sample, slightly outnumbering males (43.7%). Notably, nearly 89% of respondents revealed that they sometimes or often chat with AI, while only 1.4% had never used conversational AI. In addition, statistical analyses revealed that control variables such as age, gender, education, and usage frequency of conversational AI did not exhibit significant differences in the experimental conditions.

4.2.3. Procedures

We utilized a scenario approach. The experimental design assumed that participants purchased goods (i.e., a digital recorder) two weeks ago and now wanted to report a problem to the conversational AI for after-sales service. Our experiment was conducted by following four steps.

- Firstly, we explained the scenario to the participants and gave them a faulty digital recorder. By doing so, participants did not just gain a tangible sense of the simulated situation but could also form initial impressions about how to interact with after-sales AI in the subsequent experiment.

Table 4
Demographic characteristics of participants in the experiment (n = 142).

Demographic	Category	Freq.	%
Gender	Female	80	56.3
	Male	62	43.7
Age	18-20	30	21.1
	20-29	88	62.1
	30-39	11	7.7
	40-49	11	7.7
	Over 50 years old	2	1.4
Education	Undergraduate	83	58.4
	Master	37	26.1
	PhD	22	15.5
Usage Frequency of conversational AI	Have never used it	2	1.4
	Have tried it once or twice	7	4.9
	Use it sometimes	79	55.6
	Use it often	48	33.9
	Use it almost every day	5	3.5
	Use it everyday	1	0.7
Click on human service	Yes	81	57.0
	No	61	43.0

- Secondly, after confirming that participants had understood all information in this scenario, we asked them to complete an informed consent form and then randomly assigned them to one of the four conversational AI.

- Thirdly, we required the participants to interact with the assigned AI for at least four minutes, during which we recorded their eye-tracking data.

- Finally, we asked participants to complete a post-experimental questionnaire that measured manipulation checks (i.e., dialog length, information volume), the mediation variable (i.e., users' cognitive load, social fatigue), the dependent variable discontinuance intention and several controls. They spent approximately 20 minutes completing the survey.

4.2.4. Measures

According to the research from Zhang et al. (2016), we measured the dependent variable of discontinuance intention (Cronbach's α = 0.90). Social Fatigue (Cronbach's α = 0.91) was measured using scales adapted from Whelan et al. (2020) and Islam et al. (2020) scales. Paas and Van Merriënboer (1994) and Leppink et al. (2013) scales were used for measuring subjective Cognitive Load (Cronbach's α = 0.85) (see Table 5). We measured all items using a 7-point Likert-type scale (1 = strongly disagree; 7 = strongly agree). Moreover, we controlled for variables that could influence users' discontinuance decisions, including gender, age, usage frequency of conversational AI (Park et al., 2021), and users' attitude towards conversational AI (Cronbach's α = 0.84). Two professors and two doctoral students from the

Table 5
Measurement scales.

Construct	Item	Source
Cognitive load	During the chat with the conversational AI, I had a high level of mental effort. I think the responses language of conversational AI is very complex. I found the response/explanation of conversational AI very unclear. In terms of after-sales, I found the response/processing of conversational AI to be very ineffective.	Paas and Van Merriënboer (1994); Leppink et al. (2013)
Social fatigue	After constantly chatting with conversational AI, I found it hard to relax. I was really tired after talking with conversational AI for a while. I feel quite mentally exhausted from using conversational AI. After using conversational AI, I need to try to focus in my spare time. During the use of conversational AI, I often felt too tired to perform other active tasks.	Whelan et al. (2020); Islam et al. (2020)
Discontinuance intentions	I will use conversational AI customer service less often in the future. In future I will use human service to resolve issues. I would take a break from using conversational AI for a while and then use it again. I would stop using conversational AI if I could.	Zhang et al. (2016)
Control Variables	**Item**	**Source**
Gender	Gender: Male, Female, Other	
Age	Age (in years)	
Usage Frequency of conversational AI	Have never used it. Have tried it once or twice. Use it sometimes. Use it often. Use it almost every day. Use it every day.	Park et al. (2021)
Attitude towards conversational AI	I think conversational AI is bad (1) –good (7). I think conversational AI is unuseful (1) –useful (7). I think conversational AI is unuseful (1) –useful (7). I think conversational AI is negative (1) –positive (7).	Munnukka et al. (2022)

management discipline assessed all validity of the instrument.

Given that physiological and subjective measures can reveal different aspects of cognitive load, we also incorporated eye-tracking data into our analysis. By converting interval data (i.e., fixation duration, number of fixation points) into ordinal data through visual container separation (Cronbach's $\alpha = 0.96$), we assessed users' cognitive load. This approach tested the robustness and generalizability of our model.

4.3. Semi-structured interview

4.3.1. Interview outline

To further enrich our understanding of the consumers discontinuance of conversational AI and extend and deepen the results of the quantitative study, we conducted semi-structured interviews. The interview outline was shown in Appendix B. The interview is divided into two parts. First, we asked general questions to understand respondents' profiles. Second, specific questions from the interview outline are posed to explore users' perspectives on the factors leading to the discontinuance of conversational AI.

4.3.2. Data collection and samples

To ensure the suitability and accuracy of samples in the interview, we followed up certain participants from our experimental study. For the selection of interview subjects, we established three necessary conditions: (i) the interviewee had participated in our experimental study, (ii) their discontinuance intention score was the highest of all subjects (score greater than 5.25, full score is 7), and (iii) they had clicked the button to request human service during the experiment.

We sent interview invitations to 31 participants from the experimental study to participate in a follow-up qualitative interview, 24 participants ultimately accepted our invitation (see Table 6). This approach helps us thoroughly understand the experimental results and it also facilitates a deeper examination of users' cognition and behaviors towards conversational AI through individual cases.

Our interviews lasted 30–120 minutes, with an average of 60 minutes. We digitally recorded the interviews after obtaining consent from the participants. We then transcribed these records and forwarded the transcripts to the participants for validation.

4.3.3. Analysis procedures

We analyzed the obtained interview data using thematic analysis method, which can identify themes that are important in describing a particular phenomenon (Braun and Clarke, 2006). We carried out our thematic analysis in several steps, adhering to the guidelines provided by Braun and Clarke (2006), following the research steps outlined by Peng and Nunes (2010).

- Familiarizing with data: We proofread and re-read all collected data sets.
- Open coding: We started coding codes from the largest data collection and proceeded with the process using other collected data. Finally, 75 codes were identified.
- Connecting codes with themes: We rearranged and grouped the identified codes into 15 sub-themes and 5 themes, from which the primary categories of antecedents influencing users' discontinuance to emerge.

Table 6
Profile of interview participants (n=24).

ID	Gender	Age	Education	Usage Frequency of conversational AI	Click on human service	Discontinuance intention score
1	Male	27	PhD	Use it almost every day	Yes	7
2	Male	24	Master	Have tried it once or twice	Yes	6.25
3	Male	25	Master	Use it often	Yes	6
4	Male	21	Undergraduate	Use it sometimes	Yes	6.5
5	Female	20	Undergraduate	Use it sometimes	Yes	7
6	Male	32	PhD	Use it sometimes	Yes	6.25
7	Female	21	Undergraduate	Use it sometimes	Yes	5.25
8	Female	25	PhD	Use it often	Yes	5.75
9	Female	30	PhD	Use it sometimes	Yes	6
10	Male	29	Master	Use it almost every day	Yes	6
11	Female	18	Undergraduate	Use it often	Yes	5.5
12	Female	22	Undergraduate	Use it sometimes	Yes	5.5
13	Male	32	PhD	Use it sometimes	Yes	5.75
14	Female	20	Undergraduate	Use it sometimes	Yes	5.25
15	Male	30	PhD	Use it everyday	Yes	6
16	Male	19	Undergraduate	Use it often	Yes	5.25
17	Female	20	Undergraduate	Use it often	Yes	7
18	Female	20	Undergraduate	Use it sometimes	Yes	5.75
19	Female	18	Undergraduate	Use it sometimes	Yes	5.5
20	Male	33	PhD	Use it often	Yes	5.5
21	Female	19	Undergraduate	Use it often	Yes	6.75
22	Female	18	Undergraduate	Use it sometimes	Yes	5.5
23	Female	20	Undergraduate	Use it sometimes	Yes	5.75
24	Male	27	Master	Use it sometimes	Yes	5.25

Notes: Click on human service refers to whether participants wanted human service during our experiment (Yes means the participant clicked on the button). Discontinuance intention score adopted 7-Point Likert-type scale(1 = strongly low; 7 = strongly high).

- Reviewing themes and developing concept maps: We revisited and confirmed that all codes assigned to the themes and sub-themes followed a coherent pattern. We then generated concept maps of the analysis, which helped clarify the interrelationships among the identified driving factors.
- Reporting findings: We finally identified the themes and sub-themes and reported our findings.

5. Results

5.1. Quantitative study

5.1.1. Manipulation checks

An independent sample t-test for dialog length was conducted, showing that the mean value between long dialog and short dialog was significant (Mlong = 5.77, SDlong = 1.41, Mshort = 3.70, SDshort = 1.67, t = -7.99, p < 0.001). In addition, we conducted a manipulation check for information volume. The results showed a significant difference in mean values between high and low information (Mhigh = 5.10, SDhigh = 1.22, Mlow = 3.71, SDlow = 1.54, t = -5.96, p < 0.001). Therefore, the manipulation of dialog length and information volume was successful.

5.1.2. Descriptive Statistics and Bivariate Correlation Analysis

Table 7 presents the descriptive statistics of the variables and the correlations between them. The average score for discontinuance intention was 4.007 ± 1.391. Discontinuance intention was significantly and positively correlated with dialog length (r = 0.440, p < 0.001), information volume (r = 0.188, p < 0.05), cognitive load (r = 0.670, p < 0.001), and social fatigue (r = 0.683, p < 0.001). For the control variables, gender (r = 0.000, p > 0.05), age (r = 0.081, p > 0.05), education (r = 0.042, p > 0.05), and usage frequency (r = -0.05, p > 0.05) have no significant correlation with discontinuance intention.

Additionally, dialog length was positively correlated with cognitive load (r = 0.436, p < 0.001), social fatigue (r = 0.523, p < 0.001), and discontinuance intention (r = 0.440, p < 0.001). Likewise, information volume was positively associated with cognitive load (r = 0.253, p < 0.01), social fatigue (r = 0.169, p < 0.05), and discontinuance intention (r = 0.188, p < 0.05). Discontinuance intention was significantly and positively correlated with cognitive load (r = 0.670, p < 0.001) and social fatigue (r = 0.683, p < 0.001).

Table 7
Means, standard deviations and correlation coefficients.

Variable	Mean	SD	1	2	3	4	5	6	7	8	9
1.Gender	1.560	0.498	1								
2.Age	24.850	7.921	-0.085	1							
3.Education	4.340	1.104	-0.253**	0.313***	1						
4.Usage Frequency	3.350	0.726	-0.045	-0.226**	0.056	1					
5.Dialog Length	1.500	0.502	-0.057	-0.023	-0.166*	0.034	1				
6.Information Volume	1.514	0.502	0.138	0.097	0.092	0.061	0.014	1			
7.Cognitive Load	3.798	1.423	-0.077	0.028	0.008	0.044	0.436***	0.253**	1		
8.Social Fatigue	3.541	1.411	0.003	0.065	-0.092	0.072	0.523***	0.169*	0.654***	1	
9.Discontinuance Intention	4.007	1.391	0.000	0.081	0.042	-0.050	0.440***	0.188*	0.670***	0.683***	1

Notes: N = 217, *$p < 0.05$ (two-tailed), **$p < 0.01$(two-tailed),***$p < 0.001$(two-tailed).

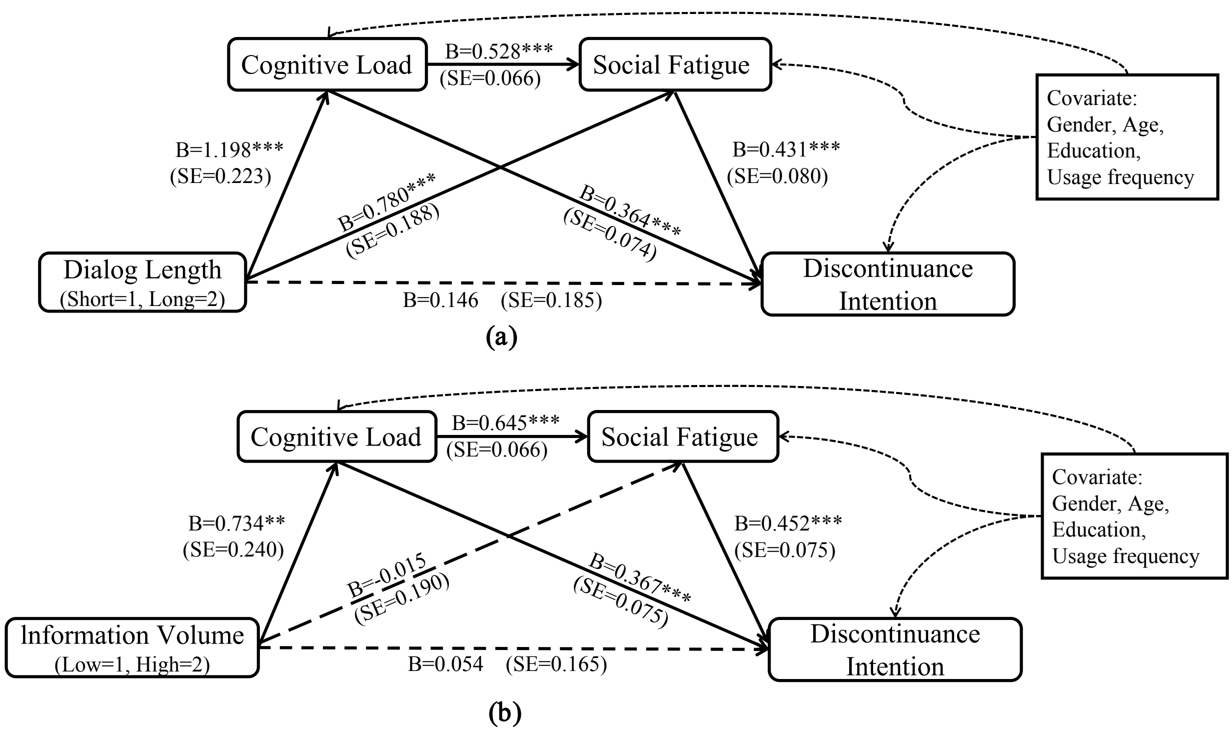


Figure 2: Two Serial Mediation Analysis Model. (a) Independent variable: Dialog Length (b) Independent variable: Information Volume. Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. B refers to unstandardized beta coefficient. SE refers to Standard Error.

5.1.3. Serial mediation analysis

To test hypotheses, two serial mediation analyses were conducted (Hayes PROCESS Macro Model 6, Bootstrapping = 5000; Hayes and Rockwood, 2020). We ran the model with dialog length and information volume as independent variables (X1 and X2), discontinuance intention as the dependent variable (Y), and cognitive load and social fatigue as the mediators. Age, gender, education, and negative emotions were entered as covariates. Table 8 presents the results of serial mediation analyses and Fig. 2 depicts the serial mediation model.

Direct effects. As shown in Table 8, the results demonstrated that dialog length was positively associated with both cognitive load (β = 1.198, SE = 0.223, 95% CI [0.757, 1.639]) and social fatigue (β = 0.780, SE = 0.188, 95% CI [0.426, 1.169]). Similarly, information volume exhibited a significant positive relationship with cognitive load (β = 0.734, SE = 0.240, 95% CI [0.260, 1.208]), whereas its association with social fatigue was negative and nonsignificant (β = -0.015, SE = 0.190, 95% CI [-0.390, 0.360]). However, neither dialog length (β = 0.146, SE = 0.185, 95% CI [-0.221, 0.512]) nor information volume (β = 0.054, SE = 0.165, 95% CI [-0.273, 0.380]) had a significant direct effect on discontinuance intention. Consequently, hypotheses H1a and H1b were not supported.

Indirect effects. The results of serial mediation analysis (Table 8) showed that when the independent variable is dialog length, the analysis revealed three main and statistically significant indirect effects: Path 1) dialog length to cognitive load to discontinuance intention was statistically significant (Indirect effect = 0.436, SE = 0.135, 95% CI [0.209, 0.733]); Path 2) dialog length to social fatigue to discontinuance

Table 8
Results of two serial mediation analyses.

Independent variables	Effect	Pathways	B	SE	95% CI	
					LL	UL
Dialog Length	Direct effects	DL → CL	1.198	0.223	0.757	1.639
		DL → SF	0.780	0.188	0.426	1.169
		CL → SF	0.528	0.066	0.398	0.657
		DL → $DI(i.e.thec'path)$	0.146	0.185	-0.221	0.512
		CL → DI	0.364	0.074	0.218	0.510
		SF → DI	0.431	0.080	0.273	0.588
	Indirect effects	DL → $CL \rightarrow DI$	0.436	0.135	0.209	0.733
		DL → $SF \rightarrow DI$	0.344	0.106	0.148	0.555
		DL → $CL \rightarrow SF \rightarrow DI$	0.272	0.088	0.125	0.468
		Total indirect effect	1.052	0.177	0.719	1.415
	Total effect	DL → DI	1.198	0.218	0.768	1.628
	Covariates	Gender → DI	0.102	0.112	-0.209	0.437
		Age → DI	0.002	0.002	-0.020	0.025
		Education → DI	0.146	0.150	-0.001	0.299
		Usage Frequency → DI	-0.177	-0.184	-0.453	0.069
Information Volume	Direct effects	IV → CL	0.734	0.240	0.260	1.208
		IV → SF	-0.015	0.190	-0.390	0.360
		CL → SF	0.645	0.066	0.516	0.775
		IV → $DI(i.e.thec'path)$	0.054	0.165	-0.273	0.380
		CL → DI	0.367	0.075	0.2188	0.515
		SF → DI	0.452	0.075	0.304	0.601
	Indirect effects	DL → $CL \rightarrow DI$	0.269	0.119	0.078	0.547
		DL → $SF \rightarrow DI$	-0.007	0.086	-0.178	0.166
		DL → $CL \rightarrow SF \rightarrow DI$	0.214	0.079	0.071	0.381
		Total indirect effect	0.477	0.182	0.124	0.840
	Total effect	DL → DI	0.530	0.239	0.059	1.002
	Covariates	Gender → DI	0.079	0.166	-0.248	0.407
		Age → DI	0.001	0.011	-0.020	0.023
		Education → DI	0.133	0.078	-0.021	0.287
		Usage Frequency → DI	-0.180	0.115	-0.407	0.047

Notes: N = 142. B refers to unstandardized coefficient; LL refers to lower limit; UL refers to upper limit; CI refers to confidence interval ((DL = Dialog Length; IV= Information Volume; CL = Cognitive Load; SF = Social Fatigue; DI = Discontinuance Intention).

intention was statistically significant (Indirect effect = 0.344, SE = 0.106, 95% CI [0.148, 0.555]); Path 3) dialog length to cognitive load to social fatigue to discontinuance intention was statistically significant (Indirect effect = 0.272, SE = 0.088, 95% CI [0.125, 0.468]). In addition, dialog length indirectly predicted discontinuance intention and was significant (Total indirect effect = 1.052, SE = 0.177, 95% CI [0.715, 1.415]). Interestingly, the direct effect of dialog length on discontinuance intention was not significant, indicating that cognitive load and social fatigue fully mediate the relationship between dialog length and discontinuance intention. H2a, H3a, and H4a were therefore supported.

When the predictor variable is information volume, the results revealed two main and statistically significant indirect effects: Path 1) information volume to cognitive load to discontinuance intention was statistically significant (Indirect effect = 0.269, SE = 0.119, 95% CI [0.078, 0.547]); Path 2) information volume to cognitive load to social fatigue to discontinuance intention was statistically significant (Indirect effect = 0.214, SE = 0.079, 95% CI [0.071, 0.381]). However, the direct effect of information volume on discontinuance intention was not significant (Direct effect = 0.054, SE = 0.165, 95% CI [-0.273, 0.380]). Thus, cognitive load and social fatigue also fully mediate the relationship between information volume and users' discontinuance intention. H2b and H4b were therefore supported, while H3b was not.

5.1.4. Robustness Test

We undertook additional robustness checks for our model to further verify our hypotheses and results. We used an alternative measurement of variables by replacing subjective data from cognitive load tasks with eye-tracking data to test all hypotheses. The robustness results demonstrated that H2, H3, and H4 were all supported, while H1 was not supported. Therefore, the robustness check results provided strong support for our quantitative findings.

5.1.5. Discussion

Our experimental study confirmed textual cues of conversational AI, as a fundamental e-service, play a crucial role in explaining user discontinuance. The results of the serial mediation analysis showed that the independent and serial mediation effects of cognitive load and social fatigue on the relationship between the independent variables (dialog length and information volume) and users' discontinuance were significant. It means that users are more likely to experience cognitive load and social fatigue when faced with long length and high-volume information in conversational AI.

More specifically, the results show that cognitive load and social fatigue have a strong positive impact on users' discontinuance intention and significantly mediate the relationship between dialog length and discontinuance intention (H2a and H3a). Similarly, cognitive load has a strong positive impact on discontinuance intention and significantly mediates the relationship between information volume and discontinuance intention (H2b). Importantly, the results suggest that dialog length and information volume affect discontinuance intention through the sequential effects of cognitive load and social fatigue (H4a and H4b). This indicates that dialog length and information volume increase cognitive load and high cognitive load increases users' social fatigue, which, in turn, results in discontinuance. This finding is consistent with previous studies that found textual cues affect users' mental effort (Schroder et al., 1967), and users' cognitive load results in social fatigue (Zhang et al., 2016; Cao and Sun, 2018; Guo et al., 2020), leading to negative decision-making and discontinuance (Fink et al., 2018; Ravindran et al., 2014). Thus, people may discontinue using conversational AI due to long dialogues and large amounts of information. In other words, people do not like long paragraphs of text and are more care about their mental and emotional expend when facing artificial intelligence.

The quantitative study advances the literature on IS discontinuance by identifying textual cues (dialog length and information volume) as novel antecedents of chatbot abandonment, mediated by cognitive load and social fatigue. Unlike prior work focusing on technical failures or user satisfaction (e.g., Zhang et al. 2016), we reveal how micro-level communication features trigger psychological strain, extending the Stimulus-Organism-Response (S-O-R) framework to AI-mediated service recovery contexts. This provides a granular understanding of why users disengage from conversational AI beyond macro-level factors (e.g., distrust or dissatisfaction).

5.2. Qualitative study

To further corroborate our experimental results and gain additional insights into users' discontinuance, semi-structured interviews and the thematic analysis were conducted to explore other driving factors for users' discontinuance. We identified 15 critical barriers, categorized into five groups: technological obstacles (3), interaction obstacles (3), readability obstacles (3), experiential obstacles (3), and psychological obstacles (3). These are detailed in Table 9. Based on the interview data and coded sub-themes, we generated a concept map illustrating the identified themes and sub-themes, as well as an obstacles model of users' discontinuance. The following subsection details the identified obstacles and their interrelationships.

5.2.1. A set of obstacles

Technological obstacles. The qualitative interview results show that conversational AI encounters severe technical difficulties and challenges, particularly in semantic recognition and language processing. Consumers generally feel that conversational AI does not automatically recognize their patterns. Specifically, it is particularly challenging to accurately identify scenarios, context, needs/requests, and emotions when consumers seek assistance: "*The conversational AI I've experienced so far hasn't been very good at understanding what I want to say*" (Interview 4). Frequently, conversational AI fails to account for the context of users' input. However, as one participant noted, "*I know the human service team won't forget what I've said before. They'll connect these sentences to understand my intent*" (Interview 14). In addition, technical defects in response and lack of technical efficiency have been other persistent issues with conversational AI. More importantly, conversational AI may give repeated answers, irrelevant replies, or commit grammatical mistakes: "*It (conversational AI) repeatedly provided redundant responses, leading me to perceive it as lacking intelligence*" (Interview 7), and "*Last time, I encountered a grammatical error in the conversational AI's response*" (Interview 1).

Interaction obstacles. We identified interaction barriers as a category that adversely influence users' continued use of conversational AI, encompassing usage complexity, difficulty, and unreasonable design/settings. Interviewees revealed that usage difficulty encompasses users' challenges with operation, typing, and icons navigation. Furthermore, the qualitative study revealed that usage complexity is also a type of interaction obstacle, arising when individuals perceive an innovation as difficult to use (Heidenreich and Spieth, 2013). For example, Interviewee 11 noted: "*My mother said that the difficulty of operating conversational AI made her think it was too complicated*"($I2 \rightarrow I1$). Some consumers also complain that conversational AI is complex to use. Interviewee 12 expressed dissatisfaction, stating, "*Following its (conversational AI) prompts to go through the return inspection process is very cumbersome*". The most concerning issue is the unreasonable design/settings of conversational AI, including unsuitable language, functionality redundancy, insufficient permissions, coercion to use, and lack of design for older adults, all of which contribute to a negative user experience. For example, consumers are always forced to use it, "*When I open the customer service interface, the system automatically activates the AI option,*

Table 9
Summary of themes and key codes.

Main themes	Sub themes	Key codes	Result in
Technological obstacles	T1: Fail to recognize user patterns automatically	T1a: Difficult to identify scenarios T1b: Difficult to identify context T1c: Difficult to identify user needs/requests T1d: Difficult to recognize user emotions	I1, I2
	T2: Technical defect of response	T2a: Incomplete corpus T2b: Irrelevant answers T2c: Repeated responses T2d: Grammatical mistakes	I1, I2
	T3: Lack of technical efficiency	T3a: Slow response T3b: Difficult to solve consumer problems	I1, E3
Interaction obstacles	I1: Usage complexity	I1a: Operation/ process complexity I1b: Interface complexity	E3
	I2: Usage difficulty	I2a: Difficult to operate I2b: Difficult to type I2c: Difficult to find the icon, interface, entry	E3, I1
	I3: Unreasonable Design/Settings	I3a: Use language of evasiveness, rote, pleasantry I3b: No aging design I3c: Functionality redundancy I3d: Insufficient permissions of conversational AI I3e: Force users to use conversational AI	I1, I2, E3
Readability obstacles	R1: Long dialog length	R1a: Long reply R1b: Dialogue complexity R1c: Users miss critical information	R3, E1, E2
	R2: High information volume	R2a: Large amounts of information R2b: Difficult for users to understand the reply R2c: Difficult for users to extract information	R3, E1
	R3: Low readability	R3a: Information irrelevance R3b: Information overload R3c: Unsmooth communication R3d: Lack of emotional reassurance	E1
Experiential obstacles	E1: Cognitive load	E1a: High mental effort E1b: Use brain power/cognitive effort	E2
	E2: Social fatigue	E2a: Anxiety/Anger E2c: Boredom E2c: Fatigue/tired/weary	P1
	E3: Dissatisfaction	E3a: Waste time/Inefficiency E3b: Sunk cost E3c: Value barriers E3d: Perceived differences	P1, P2
Psychological obstacles	P1: Psychological resistance	P1a: Consider conversational AI as tools/robots P1b: Stereotypes P1c: Poorly impressed by conversational AI	
	P2: Distrust	P2a: Distrusting belief P2b: Distrusting intentions	P1
	P3: Lack of attention to users' psychological needs	P3a: Needs to be served P3b: Needs to be valued or respected P3c: Needs to be understood	E3

compelling me to initially use the conversational AI" (Interview 5).

Readability obstacles. We grouped the readability obstacles into three separate clusters: long dialog length, high information volume, and low readability. As confirmed by the users interviewed, in addition to long dialog length, high information volume found in quantitative studies, low readability was also found to be part of readability obstacles. Low readability means information irrelevance, unsmooth communication, lack of emotional reassurance, or information overload. Consumers, already burdened with substantial daily reading tasks, may be unwilling or unable to take on additional reading responsibilities: "*For example, it constantly sends me advertisements and pushes product information, which burdens me*" (Interview 3, $R3 \rightarrow E3$). Moreover, the reply that long dialog length, high information volume and low readability can result in users having difficulty understanding, cannot extract information, and easily miss critical information: "*Sometimes it sends me a bunch of replies, but there's much* unnecessary information in between, so I can't grasp the key content clearly" (Interview 10, $R3 \rightarrow E1$).

Experiential obstacles. Technical, interactive, and readable obstacles in conversational AI may pose significant experiential obstacles for consumers. Providers and developers of conversational AI have been attempting to enhance user experience through various technical methods. However, they often overlook the significance of the user experience itself. For instance, "*Based on my previous experiences, such as feelings of anxiety and boredom, I have been badly* impressed by all AI services, so I may choose not to use it again" (Interview 22, $E2 \rightarrow P1 \rightarrow Discontinuance$), and "*The long conversations it (conversational AI) responds with cause me stress and discomfort because I need to exert energy to read through them*" (Interview 5, $R1 \rightarrow E1 \rightarrow E2$). Beyond cognitive load and social fatigue, we also identified users' dissatisfaction as a critical obstacle contributing to discontinuance. During the interview, the interviewees repetitively mentioned "waste time", "inefficiency", "sunk cost": "*It fails to address my issue entirely. it's a waste of my time and I stopped using it*"(Interview 9, $E3 \rightarrow Discontinuance$).

Psychological obstacles. Despite considerable efforts by conversational AI providers to enhance technology and improve interaction design to reassure intended consumers, consumers still exhibit high discontinuance intentions toward conversational AI. The analysis further revealed a set of psychological obstacles, which serve as the ultimate barriers to consumer engagement. Psychological obstacles consist of psychological resistance, distrust, and a lack of attention to users' psychological needs. Research confirms that psychological resistance is the most serious and immediate obstacle. Users' stereotypes and poor impressions of conversational AI, often viewing them merely as tools, directly contribute to discontinuance. For example, Interviewee 7 stated, "*My impression of them is that they can't solve my problems, so I don't think AI customer service should exist and I don't use it*" (Interview 7, $P1 \rightarrow Discontinuance$).

5.2.2. Inter-relationships between identified obstacles

This qualitative study provided a more holistic picture by exploring the intricate interrelationships among the identified sub-themes and themes, as summarized in Fig.3 and Appendix C. Those findings provide key stakeholders with an understanding of the causal relationships among challenges affecting continuous engagement with conversational AI.

As clearly shown in Appendix C, dissatisfaction emerged as a central theme on the map, with technological, interaction, and experiential obstacles identified as contributing factors. These obstacles collectively lead to consumer dissatisfaction, subsequently impacting users' trust and fostering psychological resistance to the technology. In addition, the red line in the figure corresponds to the quantitative findings, demonstrating that extended dialog length and increased information volume contribute to users' discontinuance, mediated by factors such as cognitive load and social fatigue.

By further refining the interconnections among the identified themes, we delineated a model of users discontinuance in conversational AI. We found that our model was remarkably consistent with the Stimulus-Organism-Response (S-O-R) framework (See Fig.3). The S-O-R framework suggests that individuals can respond to environmental stimuli and develop emotional and cognitive conditions that ultimately lead to specific behavioral outcomes (Lin and Wang, 2023; Jacoby, 2002). This study found that the challenge of users' discontinuance stems from a variety of technological, interaction, readability, experiential, and psychological obstacles. In fact, we observed that there was a sequential cascade of effects among the identified obstacles. Stimuli encompass technological obstacles, interaction obstacles, and readability obstacles in the context of users' continuous engagement in conversational AI. These stimuli serve as main drivers for users to form experiential and psychological obstacles (i.e., the organism). Subsequently, these experiential and psychological obstacles directly precipitate user discontinuance (i.e., the response) to conversational AI.

6. Conclusions and implications

6.1. The primary findings

Our mixed-methods findings reveal a multi-layered discontinuance mechanism in which micro-level textual cues (RQ1) and a macro-level set of obstacles (RQ2) jointly drive user abandonment. And our study provides a comprehensive, multi-layered understanding of conversational AI discontinuance, highlighting factors leading to discontinuance based on cognitive psychology and behavioral science. We summarize our findings in response to the research questions posed.

RQ1. This experimental study illuminated the textual preferences of customers during interactions with service-oriented chatbots, highlighting the critical role of textual cues in conversational AI. We found that factors such as dialog length and information volume are pivotal in influencing users' decisions to discontinue the use of conversational AI. Additionally, our research demonstrates that user cognitive load and social fatigue act as sequential mediators in this relationship. Specifically, consumers show a marked preference for concise responses from conversational AI. This preference is motivated by the recognition that lengthy and information-dense replies can increase cognitive load and induce social fatigue, which, in turn, trigger discontinuance intentions.

RQ2. Through interviews and subsequent thematic analysis, we identified five categories of obstacles that contribute to discontinuance in conversational AI: technological, interaction, readability, experiential, and psychological obstacles. Our analysis reveals a network of interrelationships among these obstacles, in which technological obstacles serve as the primary source, directly leading to interaction obstacles. Furthermore, technological, interaction, and readability obstacles collectively influence discontinuance

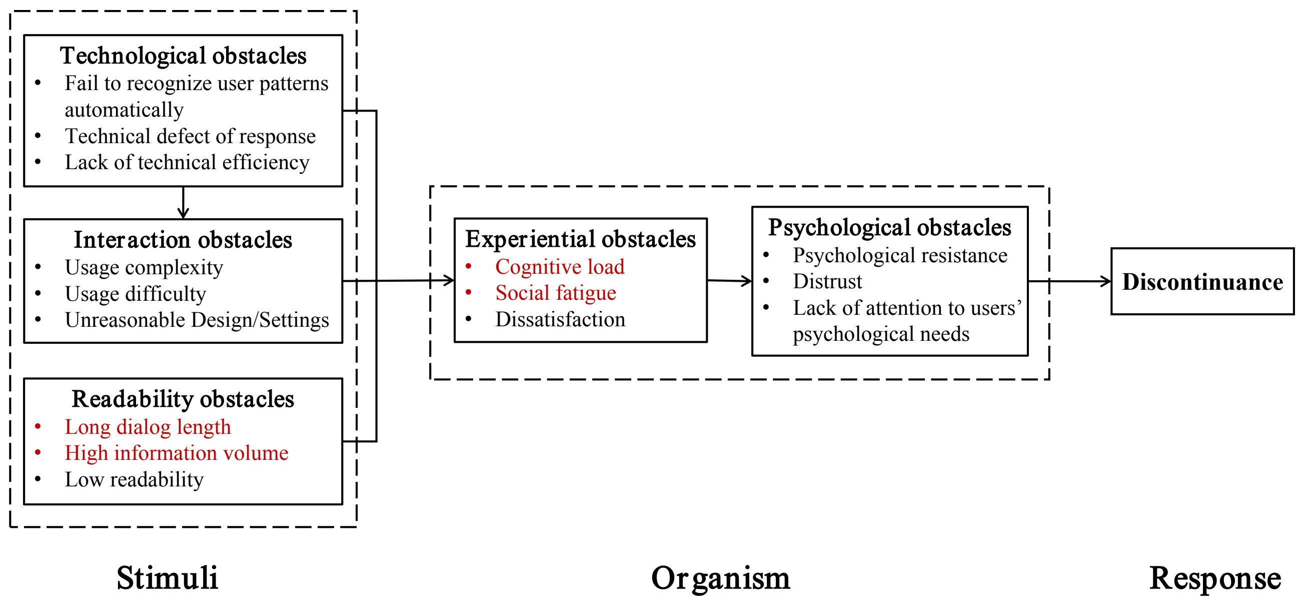


Figure 3: Inter-relationships between identified obstacles. Note: The red sub-themes echoed the quantitative studies.

by impacting both experiential and psychological obstacles. This pattern of influence aligns with the Stimulus-Organism-Response (SOR) framework. Specifically, external stimuli (technological, interaction, and readability obstacles) affect user behaviors (discontinuance of conversational AI) through intervening cognitive and affective organism states (experiential and psychological obstacles), thus corroborating the SOR model in this context.

6.2. Theoretical implications

There are several important theoretical implications in this study. First, we contribute to the IS discontinuance literature by highlighting the critical yet underexplored role of textual cues, whereas previous research has primarily focused on technological issues (Zamani and Pouloudi, 2021; Cenfetelli, 2004), information-related factors (Cenfetelli and Schwarz, 2011), and user psychological factors (Cao and Sun, 2018; Ravindran et al., 2014; Zhang et al., 2016). Our findings demonstrate that textual cues—specifically dialog length and information density—serve as significant antecedents of discontinuance in conversational AI, fully mediated by cognitive load and social fatigue. When "dialog becomes excessively long or overly dense with information", users are more likely to disengage, leading to chatbot discontinuance. This finding extends prior work on IS discontinuance (e.g., Zhang et al., 2016) by revealing that prolonged exposure to poorly designed textual interactions can independently drive abandonment, even when the chatbot functionally succeeds. This shifts the focus from "what AI does" to "how AI communicates".

Second, this study enriches the understanding of psychological impacts—specially, cognitive load and social fatigue—in the context of conversational AI. Prior research has studied the role of social fatigue in discontinuance intentions (Ravindran et al., 2014; Zhang et al., 2016; Cao and Sun, 2018). However, the mediating effects of these psychological factors—linking textual cues to discontinuance—have not been adequately examined. Our study extends this body of knowledge by demonstrating that the dialog length and information density in conversational AI can significantly contribute to users' cognitive load and social fatigue, which in turn trigger users' discontinuance. This offers valuable insights into the psychological and cognitive factors (e.g., cognitive load and social fatigue) that are likely to elicit specific behaviors in conversational AI usage.

Finally, this study advances the S-O-R framework by applying it to the relatively new phenomenon of user behavior toward conversational AI. The study validates and refines the applicability of the S-O-R framework in understanding user discontinuance: we map technological, interaction and readability-related challenges as stimuli; experiential and psychological obstacles as organism states; and chatbot discontinuance as the response. Drawing on prior literature (Jacoby, 2002; Cao and Sun, 2018) and our conceptualization, we clarify how technological obstacles, interaction obstacles, and readability obstacles as stimuli components translate into experiential and psychological obstacles, ultimately leading to user withdrawal. This enhanced understanding could help future researchers explore the complexities of users' discontinuance from a more holistic and integrative perspective, further enriching the discourse on user engagement and retention in technology use.

6.3. Practical implications

From a practical perspective, our findings provide actionable recommendations for both users and providers of conversational AI.

First, the results of this study stress the importance for service companies to consider textual cues carefully when deploying conversational AI during service recovery processes, as these cues significantly impact customers' perceptions and behavioral intentions. For example, extended dialogues and higher information density can lead to increased cognitive load and social fatigue, thereby positively affecting users' propensity to discontinue using conversational AI. This insight is crucial for the design and deployment of conversational AI, suggesting that developers should optimize customer service interactions by designing reasonable conversation patterns and employing appropriate textual cues. We suggest that developers and service providers can introduce real-time fatigue detection mechanisms in conversational AI systems, utilizing sentiment analysis to identify user cognitive load and social fatigue through measurable behavioral indicators such as repeated queries, users' response time, and score for the reply. Upon detection, the system should either reallocate computational resources or deploy cached responses and trigger automatic dialogue simplification or human service. These design guidelines ensures continuous system improvement based on actual user interaction patterns, and fully considers the impact of textual cues on user interactions.

Second, our research offers practitioners a preliminary understanding of users' discontinuance of conversational AI, highlighting the occurrence of such behaviors during customer engagement process. While the positive consequences (e.g., labor cost savings and increased transaction volumes) of conversational AI use have gained growing traction, its negative consequences have been relatively overlooked. It is essential for practitioners to understand the reasons behind users' discontinuance to devise effective management strategies. For e-commerce companies utilizing conversational AI, crafting responses to be brief and to the point during customer interactions can mitigate users' cognitive load and enhance their overall user experience. Therefore, practitioners can apply the "7 ± 2 principle", which involves limiting each message to 5-9 information chunks (Miller, 1956) and checking reply readability to reduce users' cognitive load. Additionally, in instances where AI fails to deliver the expected service outcome, promptly transitioning the user to a human service can prevent further aggravation of users' experiential and psychological barriers. Our findings provide insights into mitigating users' dissatisfaction with conversational AI.

Finally, for customers, our research offers insights into the psychological processes associated with using AI and the challenges in AI promotion. We hope that users of conversational AI will recognize the limitations of these systems and provide them with more opportunities for service enhancements and room for improvement. This understanding could create a more tolerant and supportive environment for the evolution of conversational AI.

7. Limitations, future work, and concluding remarks

While this study contributes significantly to knowledge, it nonetheless has several limitations. First, most of our interviewees were under 40 years old. This demographic profile likely influenced our results, especially regarding the distinctions between digital immigrants and digital natives. Notably, our qualitative research participants were sampled from experimental subjects with a marked intention to discontinue using conversational AI. Older participants in the study showed a lower intention to discontinue than their younger counterparts. We submit that future research should delve deeper into this issue, as understanding discontinuance across different digital generations could yield valuable insights for both theory and practice. Second, the study was carried out in the context of China, suggesting that the identified challenges and their interconnections might be more relevant to China and countries with similar characteristics, such as comparable economic systems. An intriguing direction for future research would be to validate and test these findings in other geographical contexts beyond China.

From a cognitive psychology and behavioral science perspective, this paper examined the phenomenon of users' discontinuance of conversational AI and its driving obstacles through a sequential mixed-methods approach. Our findings indicate that focusing solely on technological innovation and development may not resolve the issue of discontinuous use. Addressing the psychological and experiential obstacles users face with AI is crucial. The recent global surge in ChatGPT adoption is a testament to the disruptive potential of AI technology (Dwivedi et al., 2023), but research on the discontinuance of conversational AI remains sparse (Mariani et al., 2023). Given ChatGPT's booming growth, it is vital to validate our findings through future research specifically focused on ChatGPT. Additionally, despite the rapid development of ChatGPT, it presents challenges such as logical inconsistencies, inaccurate content, and a lack of originality (Dwivedi et al., 2023). Future research could shift towards exploring how these negative aspects impact user discontinuance, building on our model.

Conversational AI like ChatGPT has the potential to significantly influence our online behaviors, with far-reaching implications for social and organizational dynamics. As AI-powered conversational agents grow more sophisticated, their role in facilitating meaningful interactions and decision-making processes is likely to increase. However, it is critical to acknowledge both the opportunities and challenges posed by ChatGPT in the realm of interpersonal communication, collaboration, and knowledge sharing. By examining the ethical, technical, and socio-organizational dimensions of AI-assisted communication, we can leverage the advantages of ChatGPT while addressing potential pitfalls. Finally, the evolution of online behaviors and interactions will depend not only on the capabilities of conversational AI but also on the proactive involvement of users, researchers, and policymakers in co-fostering a responsible and inclusive digital ecosystem.

CRediT authorship contribution statement

Siyuan Wu: Conceptualization, Methodology, Investigation, Formal analyses, Data curation, Writing - Original Draft, Writing - Review and Editing. **Guochao Peng:** Conceptualization, Methodology, Resources, Writing - Original Draft. **Shuyang Li:** Conceptualization, Methodology, Writing - Review and Editing. **David Cameron:** Methodology, Writing - Review. **Jun Zhang:** Conceptualization, Methodology, Writing - Review, Editing. **Justin Zhang:** Validation, Editing. **Qing Zhang:** Editing.

Funding

This work was supported by the National Natural Science Foundation of China (grant numbers 72474236).

References

Araujo, T., 2018. Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. Computers in human behavior 85, 183–189.

Ashfaq, M., Yun, J., Yu, S., Loureiro, S.M.C., 2020. I, chatbot: Modeling the determinants of users' satisfaction and continuance intention of ai-powered service agents. Telematics and Informatics 54, 101473.

Bailin, A., Grafstein, A., 2001. The linguistic assumptions underlying readability formulae: A critique. Language & communication 21, 285–301.

Brachten, F., Kissmer, T., Stieglitz, S., 2021. The acceptance of chatbots in an enterprise context–a survey study. International Journal of Information Management 60, 102375.

Brandtzaeg, P.B., Følstad, A., 2018. Chatbots: changing user needs and motivations. interactions 25, 38–43.

Braun, V., Clarke, V., 2006. Using thematic analysis in psychology. Qualitative research in psychology 3, 77–101.

Bright, L.F., Kleiser, S.B., Grau, S.L., 2015. Too much facebook? an exploratory examination of social media fatigue. Computers in Human Behavior 44, 148–155.

Cao, X., Sun, J., 2018. Exploring the effect of overload on the discontinuous intention of social media users: An sor perspective. Computers in human behavior 81, 10–18.

Cassell, J., 2001. Embodied conversational agents: representation and intelligence in user interfaces. AI magazine 22, 67–67.

Castillo, D., Canhoto, A.I., Said, E., 2021. The dark side of ai-powered service interactions: Exploring the process of co-destruction from the customer perspective. The Service Industries Journal 41, 900–925.

Cenfetelli, R.T., 2004. Inhibitors and enablers as dual factor concepts in technology usage. Journal of the Association for Information Systems 5, 16.

Cenfetelli, R.T., Schwarz, A., 2011. Identifying and testing the inhibitors of technology usage intentions. Information systems research 22, 808–823.

Chandra, S., Shirish, A., Srivastava, S.C., 2022. To be or not to be… human? theorizing the role of human-like competencies in conversational artificial intelligence agents. Journal of Management Information Systems 39, 969–1005.

Chen, J.S., Le, T.T.Y., Florence, D., 2021. Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing. International Journal of Retail & Distribution Management 49, 1512–1531.

Chen, J.V., Tran, A., Nguyen, T., 2019. Understanding the discontinuance behavior of mobile shoppers as a consequence of technostress: An application of the stress-coping theory. Computers in Human Behavior 95, 83–93.

Chen, Q., Gong, Y., Lu, Y., Luo, X., 2024. The golden zone of ai's emotional expression in frontline chatbot service failures. Internet Research .

Chen, Q., Lu, Y., Gong, Y., Xiong, J., 2023. Can ai chatbots help retain customers? impact of ai service quality on customer loyalty. Internet Research .

Chen, X., Meurers, D., 2018. Word frequency and readability: Predicting the text-level readability with a lexical-level attribute. Journal of Research in Reading 41, 486–510.

Ciechanowski, L., Przegalinska, A., Magnuski, M., Gloor, P., 2019. In the shades of the uncanny valley: An experimental study of human–chatbot interaction. Future Generation Computer Systems 92, 539–548.

Colace, F., De Santo, M., Pascale, F., Lemma, S., Lombardi, M., et al., 2017. Botwheels: a petri net based chatbot for recommending tires. DATA 17, 350–358.

Cook, T.D., Campbell, D.T., Shadish, W., 2002. Experimental and quasi-experimental designs for generalized causal inference. volume 1195. Houghton Mifflin Boston, MA.

Creswell, J.W., Creswell, J.D., 2017. Research design: Qualitative, quantitative, and mixed methods approaches. Sage publications.

Crisafulli, B., Singh, J., 2017. Service failures in e-retailing: Examining the effects of response time, compensation, and service criticality. Computers in Human Behavior 77, 413–424.

Crossler, R.E., Johnston, A.C., Lowry, P.B., Hu, Q., Warkentin, M., Baskerville, R., 2013. Future directions for behavioral information security research. computers & security 32, 90–101.

Crossley, S.A., Greenfield, J., McNamara, D.S., 2008. Assessing text readability using cognitively based indices. Tesol Quarterly 42, 475–493.

Davenport, T., Guha, A., Grewal, D., Bressgott, T., 2020. How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science 48, 24–42.

Davis, T.C., Dolan, N.C., Ferreira, M.R., Tomori, C., Green, K.W., Sipler, A.M., Bennett, C.L., 2001. The role of inadequate health literacy skills in colorectal cancer screening. Cancer investigation 19, 193–200.

Divya, S., Indumathi, V., Ishwarya, S., Priyasankari, M., Devi, S.K., 2018. A self-diagnosis medical chatbot using artificial intelligence. Journal of Web Development and Web Designing 3, 1–7.

Driver, M.J., Mock, T.J., 1975. Human information processing, decision style theory, and accounting information systems. The Accounting Review 50, 490–508.

Dubay, W.H., 2004. The principles of readability. impact information. Costa Mesa, CA .

Duong, C.D., Vu, T.N., Ngo, T.V.N., Do, N.D., Tran, N.M., 2024. Reduced student life satisfaction and academic performance: Unraveling the dark side of chatgpt in the higher education context. International Journal of Human–Computer Interaction , 1–16.

Dwivedi, Y.K., Kshetri, N., Hughes, L., Slade, E.L., Jeyaraj, A., Kar, A.K., Baabdullah, A.M., Koohang, A., Raghavan, V., Ahuja, M., et al., 2023. "so what if chatgpt wrote it?" multidisciplinary perspectives on opportunities, challenges and implications of generative conversational ai for research, practice and policy. International Journal of Information Management 71, 102642.

Faul, F., Erdfelder, E., Lang, A.G., Buchner, A., 2007. G* power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. Behavior research methods 39, 175–191.

Feine, J., Gnewuch, U., Morana, S., Maedche, A., 2019. A taxonomy of social cues for conversational agents. International Journal of Human-Computer Studies 132, 138–161.

Fink, L., Rosenfeld, L., Ravid, G., 2018. Longer online reviews are not necessarily better. International Journal of Information Management 39, 30–37.

Flesch, R., 1948. A new readability yardstick. Journal of applied psychology 32, 221.

Friedman, D.B., Hoffman-Goetz, L., 2006. A systematic review of readability and comprehension instruments used for print and web-based cancer information. Health Education & Behavior 33, 352–373.

Furneaux, B., Wade, M.R., 2011. An exploration of organizational level information systems discontinuance intentions. Mis Quarterly , 573–598.

Genzel, D., Charniak, E., 2002. Entropy rate constancy in text, in: Proceedings of the 40th annual meeting of the Association for Computational Linguistics, pp. 199–206.

Ghazali, A.S., Ham, J., Barakova, E., Markopoulos, P., 2018. The influence of social cues in persuasive social robots on psychological reactance and compliance. Computers in Human Behavior 87, 58–65.

Gkinko, L., Elbanna, A., 2023. The appropriation of conversational ai in the workplace: A taxonomy of ai chatbot users. International Journal of Information Management 69, 102568.

Go, E., Sundar, S.S., 2019. Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions. Computers in Human Behavior 97, 304–316.

Golan, A., 2002. Information and entropy econometrics—editor's view. Journal of econometrics 107, 1–15.

Grimes, G.M., Schuetzler, R.M., Giboney, J.S., 2021. Mental models and expectation violations in conversational ai interactions. Decision Support Systems 144, 113515.

Guo, Y., Lu, Z., Kuang, H., Wang, C., 2020. Information avoidance behavior on social network sites: Information irrelevance, overload, and the moderating role of time pressure. International Journal of Information Management 52, 102067.

Haas, D.F., Kraft, D.H., 1984. Experimental and quasi-experimental designs for research in information science. Information Processing & Management 20, 229–237.

Hancock, J.T., Dunham, P.J., 2001. Impression formation in computer-mediated communication revisited: An analysis of the breadth and intensity of impressions. Communication research 28, 325–347.

Hayes, A.F., Rockwood, N.J., 2020. Conditional process analysis: Concepts, computation, and advances in the modeling of the contingencies of mechanisms. American Behavioral Scientist 64, 19–54.

Heidenreich, S., Handrich, M., 2015. What about passive innovation resistance? investigating adoption-related behavior from a resistance perspective. Journal of Product Innovation Management 32, 878–903.

Heidenreich, S., Spieth, P., 2013. Why innovations fail—the case of passive and active innovation resistance. International Journal of Innovation Management 17, 1350021.

Honora, A., Chih, W.H., Wang, K.Y., 2022. Managing social media recovery: The important role of service recovery transparency in retaining customers. Journal of Retailing and Consumer Services 64, 102814.

Hsu, C.L., Lin, J.C.C., 2023. Understanding the user satisfaction and loyalty of customer service chatbots. Journal of Retailing and Consumer Services 71, 103211.

Huang, Y., Gursoy, D., Zhang, M., Nunkoo, R., Shi, S., 2021. Interactivity in online chat: Conversational cues and visual cues in the service recovery process. International Journal of Information Management 60, 102360.

Islam, A.N., Laato, S., Talukder, S., Sutinen, E., 2020. Misinformation sharing and social media fatigue during covid-19: An affordance and cognitive load perspective. Technological forecasting and social change 159, 120201.

Ivankova, N.V., 2014. Implementing quality criteria in designing and conducting a sequential quan→ qual mixed methods study of student engagement with learning applied research methods online. Journal of Mixed Methods Research 8, 25–51.

Jacoby, J., 2002. Stimulus-organism-response reconsidered: an evolutionary step in modeling (consumer) behavior. Journal of consumer psychology 12, 51–57.

Jaeger, T.F., 2010. Redundancy and reduction: Speakers manage syntactic information density. Cognitive psychology 61, 23–62.

Jiang, Y., Yang, X., Zheng, T., 2023. Make chatbots more adaptive: Dual pathways linking human-like cues and tailored response to trust in interactions with chatbots. Computers in Human Behavior 138, 107485.

Jones, Q., Ravid, G., Rafaeli, S., 2004. Information overload and the message dynamics of online interaction spaces: A theoretical model and empirical exploration. Information systems research 15, 194–210.

Kang, K., Lu, J., Guo, L., Li, W., 2021. The dynamic effect of interactivity on customer engagement behavior through tie strength: Evidence from live streaming commerce platforms. International Journal of Information Management 56, 102251.

Khan, A.K., Singh, R., Bhadury, J., 2024. Perceived response failure of mental health chatbots: Conceptualization and consequences on discontinuance .

Kuan, K.K., Hui, K.L., Prasarnphanich, P., Lai, H.Y., 2015. What makes a review voted? an empirical investigation of review voting in online review systems. Journal of the Association for Information Systems 16, 1.

Laumer, S., Maier, C., Gubler, F.T., 2019. Chatbot acceptance in healthcare: Explaining user adoption of conversational agents for disease diagnosis .

Lee, A.R., Son, S.M., Kim, K.K., 2016. Information and communication technology overload and social networking service fatigue: A stress perspective. Computers in human behavior 55, 51–61.

Leppink, J., Paas, F., Van der Vleuten, C.P., Van Gog, T., Van Merriënboer, J.J., 2013. Development of an instrument for measuring different types of cognitive load. Behavior research methods 45, 1058–1072.

Leroy, G., Helmreich, S., Cowie, J.R., 2010. The influence of text characteristics on perceived and actual difficulty of health information. International journal of medical informatics 79, 438–449.

Li, Y.M., Lai, C.Y., Chen, C.W., 2011. Discovering influencers for marketing in the blogosphere. Information Sciences 181, 5143–5157.

Lin, X., Wang, X., 2023. Following too much on facebook brand page: A concept of brand overload and its validation. International Journal of Information Management 73, 102682.

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

Maier, C., Laumer, S., Eckhardt, A., Weitzel, T., 2015a. Giving too much social support: social overload on social networking sites. European Journal of Information Systems 24, 447–464.

Maier, C., Laumer, S., Weinert, C., Weitzel, T., 2015b. The effects of technostress and switching stress on discontinued use of social networking services: a study of facebook use. Information Systems Journal 25, 275–308.

Mariani, M.M., Machado, I., Nambisan, S., 2023. Types of innovation and artificial intelligence: A systematic quantitative literature review and research agenda. Journal of Business Research 155, 113364.

Miller, G.A., 1956. The magical number seven, plus or minus two: Some limits on our capacity for processing information. Psychological review 63, 81.

Moffett, J.W., Folse, J.A.G., Palmatier, R.W., 2021. A theory of multiformat communication: mechanisms, dynamics, and strategies. Journal of the Academy of Marketing Science 49, 441–461.

Munnukka, J., Talvitie-Lamberg, K., Maity, D., 2022. Anthropomorphism and social presence in human–virtual service assistant interactions: The role of dialog length and attitudes. Computers in Human Behavior 135, 107343.

Nattkemper, D., Prinz, W., 1990. Local and global control of saccade amplitude and fixation duration in continuous visual search. .

Nguyen, T., et al., 2019. Potential effects of chatbot technology on customer support: A case study .

Paas, F.G., Van Merriënboer, J.J., 1994. Variability of worked examples and transfer of geometrical problem-solving skills: A cognitive-load approach. Journal of educational psychology 86, 122.

Park, N., Jang, K., Cho, S., Choi, J., 2021. Use of offensive language in human-artificial intelligence chatbot interaction: The effects of ethical ideology, social competence, and perceived humanlikeness. Computers in Human Behavior 121, 106795.

Peng, G.C., Nunes, M.B., 2010. Exploring cultural impact on long-term utilization of enterprise systems, in: 2010 43rd Hawaii International Conference on System Sciences, IEEE. pp. 1–10.

Pillai, R., Sivathanu, B., 2020. Adoption of ai-based chatbots for hospitality and tourism. International Journal of Contemporary Hospitality Management 32, 3199–3226.

Przegalinska, A., Ciechanowski, L., Stroz, A., Gloor, P., Mazurek, G., 2019. In bot we trust: A new methodology of chatbot performance measures. Business Horizons 62, 785–797.

Rai, A., 2020. Explainable ai: From black box to glass box. Journal of the Academy of Marketing Science 48, 137–141.

Ravindran, T., Yeow Kuan, A.C., Hoe Lian, D.G., 2014. Antecedents and effects of social network fatigue. Journal of the Association for Information Science and Technology 65, 2306–2320.

Rese, A., Ganster, L., Baier, D., 2020. Chatbots in retailers' customer communication: How to measure their acceptance? Journal of Retailing and Consumer Services 56, 102176.

Rudroff, T., 2024. Revealing the complexity of fatigue: a review of the persistent challenges and promises of artificial intelligence. Brain sciences 14, 186.

Sachdeva, A., Kim, A., Dennis, A.R., 2024. Taking the chat out of chatbot? collecting user reviews with chatbots and web forms. Journal of Management Information Systems 41, 146–177.

Schroder, H.M., Driver, M.J., Streufert, S., 1967. Human information processing: Individuals and groups functioning in complex social situations. (No Title) .

Schuetzler, R.M., Grimes, G.M., Scott Giboney, J., 2020. The impact of chatbot conversational skill on engagement and perceived humanness. Journal of Management Information Systems 37, 875–900.

Shannon, C.E., 1948. A mathematical theory of communication. The Bell system technical journal 27, 379–423.

Shi, Y., Xu, A.T., 2024. From enthusiasm to fatigue: Exploring reduced use and gratification dynamics in intelligent system collaboration .

Smith, A.K., Bolton, R.N., Wagner, J., 1999. A model of customer satisfaction with service encounters involving failure and recovery. Journal of marketing research 36, 356–372.

Soliman, W., Rinta-Kahila, T., 2020. Toward a refined conceptualization of is discontinuance: Reflection on the past and a way forward. Information & Management 57, 103167.

Soliman, W., Tuunainen, V.K., 2022. A tale of two frames: Exploring the role of framing in the use discontinuance of volitionally adopted technology. Information Systems Journal 32, 473–519.

Steiner, P.M., Cook, T.D., Shadish, W.R., Clark, M.H., 2010. The importance of covariate selection in controlling for selection bias in observational studies. Psychological methods 15, 250.

Sun, Y., Li, S., Yu, L., 2022. The dark sides of ai personal assistant: effects of service failure on user continuance intention. Electronic Markets 32, 17–39.

Teddlie, C., Tashakkori, A., 2003. Major issues and controversies in the use of mixed methods in the social and behavioral sciences. Handbook of mixed methods in social and behavioral research 1, 13–50.

Toader, D.C., Boca, G., Toader, R., Măcelaru, M., Toader, C., Ighian, D., Rădulescu, A.T., 2019. The effect of social presence and chatbot errors on trust. Sustainability 12, 256.

Tversky, A., Kahneman, D., 1974. Judgment under uncertainty: Heuristics and biases: Biases in judgments reveal some heuristics of thinking under uncertainty. science 185, 1124–1131.

Venkatesh, V., Brown, S.A., Bala, H., 2013. Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. MIS quarterly , 21–54.

Walther, J.B., 2006. Nonverbal dynamics in computer-mediated communication, or:(and the net:('s with you:) and you:) alone. Handbook of nonverbal communication , 461–479.

Wedel, M., Kannan, P., 2016. Marketing analytics for data-rich environments. Journal of marketing 80, 97–121.

Weiler, S., Matt, C., Hess, T., 2022. Immunizing with information–inoculation messages against conversational agents' response failures. Electronic Markets 32, 239–258.

Whelan, E., Najmul Islam, A., Brooks, S., 2020. Is boredom proneness related to social media overload and fatigue? a stress–strain–outcome approach. Internet Research 30, 869–887.

Wong, A., Leahy, W., Marcus, N., Sweller, J., 2012. Cognitive load theory, the transient information effect and e-learning. Learning and instruction 22, 449–457.

Yankouskaya, A., Liebherr, M., Ali, R., 2025. Can chatgpt be addictive? a call to examine the shift from support to dependence in ai conversational large language models. Human-Centric Intelligent Systems , 1–13.

Yao, J., Cao, X., 2017. The balancing mechanism of social networking overuse and rational usage. Computers in Human Behavior 75, 415–422.

Zagermann, J., Pfeil, U., Reiterer, H., 2016. Measuring cognitive load using eye tracking technology in visual computing, in: Proceedings of the sixth workshop on beyond time and errors on novel evaluation methods for visualization, pp. 78–85.

Zamani, E.D., Pouloudi, N., 2021. Generative mechanisms of workarounds, discontinuance and reframing: a study of negative disconfirmation with consumerised it. Information Systems Journal 31, 384–428.

Zhang, C., Pan, S., Zhao, Y., 2024. More is not always better: Examining the drivers of livestream sales from an information overload perspective. Journal of Retailing and Consumer Services 77, 103651.

Zhang, S., Zhao, L., Lu, Y., Yang, J., 2016. Do you get tired of socializing? an empirical explanation of discontinuous usage behaviour in social network services. Information & Management 53, 904–914.

Zhang, T., Tong, Q., 2024. The technostress of chatgpt usage: How do perceived ai characteristics affect user discontinuous usage through ai anxiety and user negative attitudes? International Journal of Human–Computer Interaction , 1–12.

Zhou, C., Chang, Q., 2024. Informational or emotional? exploring the relative effects of chatbots' self-recovery strategies on consumer satisfaction. Journal of Retailing and Consumer Services 78, 103779.

Zhu, Y., Zhang, J., Wu, J., Liu, Y., 2022. Ai is better when i'm sure: The influence of certainty of needs on consumers' acceptance of ai chatbots. Journal of Business Research 150, 642–652.

Ziefle, M., Oehme, O., Luczak, H., 2005. Information presentation and visual performance in head mounted displays with augmented reality. Zeitschrift fur Arbeitswissenschaft 59, 331.

A. Appendix. Experiment stimuli materials

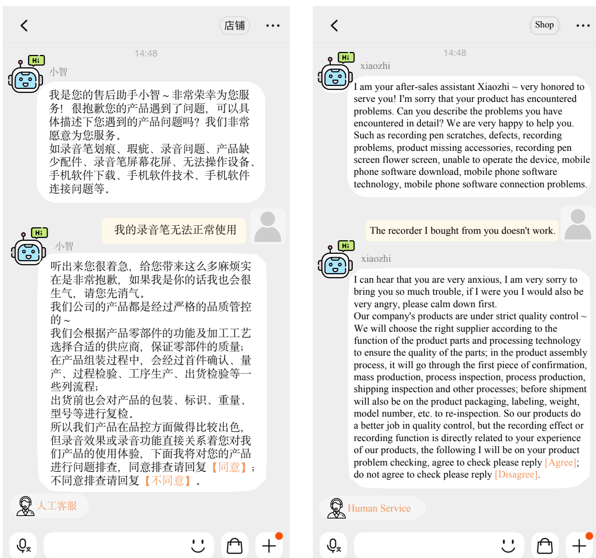
The following are experiment stimuli materials (question and answer interaction in four different conversational AI prototypes, Figure A.1 , Figure A.2 , Figure A.3 , and Figure A.4).

B. Appendix. Semi-structured interview protocol

C. Appendix. Inter-relationships between identified sub-themes in qualitative study

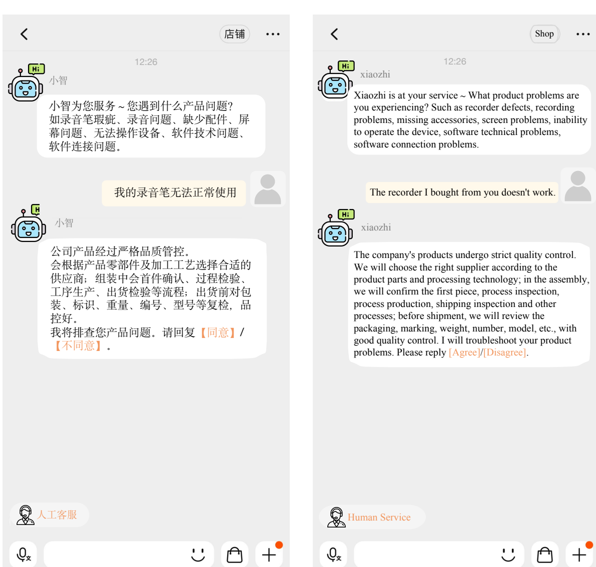
Semi-structured interview protocol.

	Question
General Questions	Gender, Age, Education, Usage Frequency of conversational AI
Interview Outline	Why did you click on human service during our experiment?
	For what reasons will you start to reduce/stop/resist using conversational AI? (Can you give any examples of the change?)
	What aspects of conversational AI are you disappointed/unhappy with?
	How will your emotions affect your discontinuance?
	How do you believe the textual features of conversational AI will influence your usage?
	How do your past negative experiences with conversational AI impact your current use of it?



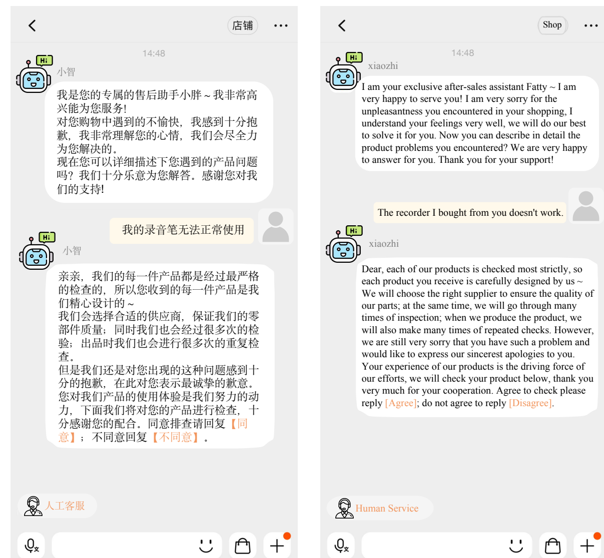
(a) (b)

Figure A.1: Example of conversational AI of type A (long dialog and high information). The picture (a) is Chinese version, picture (b) is English version.



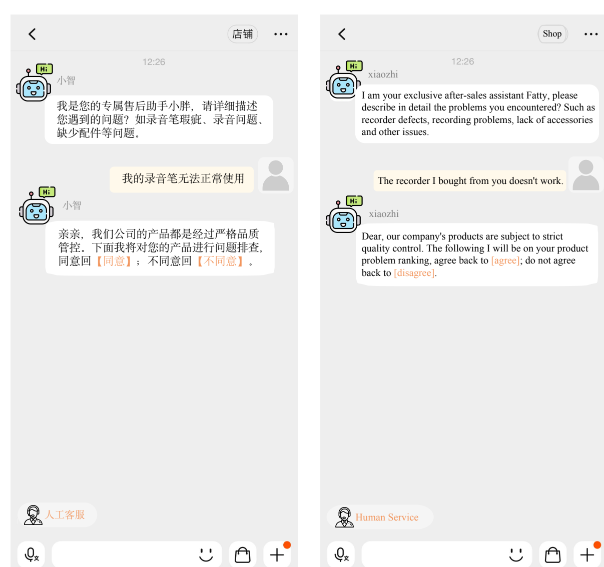
(a) (b)

Figure A.2: Example of conversational AI of type B (short dialog and high information). The picture (a) is Chinese version, picture (b) is English version.



(a) (b)

Figure A.3: Example of conversational AI of type C (long dialog and low information). The picture (a) is Chinese version, picture (b) is English version.



(a) (b)

Figure A.4: Example of conversational AI of type D (short dialog and low information). The picture (a) is Chinese version, picture (b) is English version.

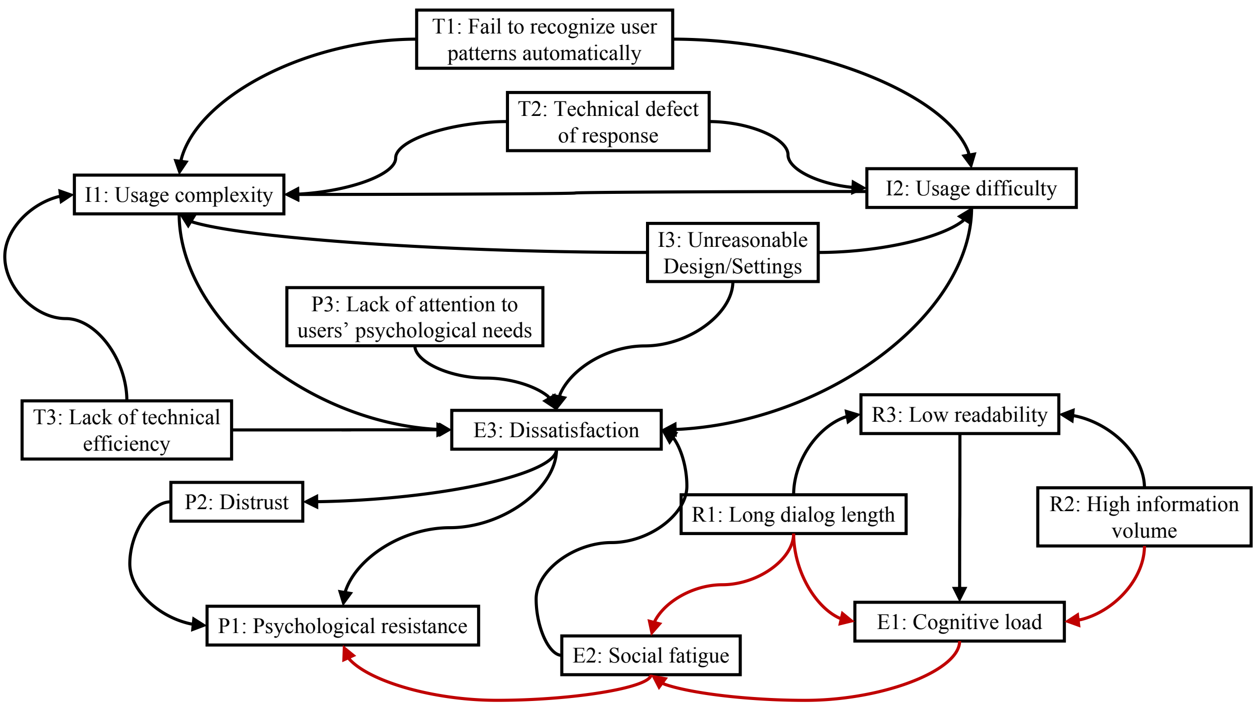


Figure C: Inter-relationships between identified sub-themes. Notes: The red line also echoed the results of quantitative studies.