FEELING YOUR HEART: THE EFFECTS OF THE PERCEIVED AGENT EMPATHIC CAPABILITY ON USERS' CONTINUOUS USE INTENTION

Mukun Cao
School of Management
Xiamen University
No. 422 Siming South Road, Siming District, Xiamen 361005, China
mkcao@xmu.edu.cn

Lei Xian
School of Management
Xiamen University
No. 422 Siming South Road, Siming District, Xiamen 361005, China
xianlei@stu.xmu.edu.cn

Ya Zhou[1]
School of Management
Xiamen University
No. 422 Siming South Road, Siming District, Xiamen 361005, China
zhouya@xmu.edu.cn

ABSTRACT

Negotiation, a time-consuming process, necessitates empathy to resolve conflicts and reach agreements. While AI-based automated agents gain prevalence in e-commerce, our understanding of how the evolution of empathic agents could function in human-to-agent negotiation is still lacking. Motivated thus, this study, drawing on social response theory and empathy literature, develops a research model to investigate how the user-perceived negotiation agent's empathic capability could influence their continuous use intention. The research model is tested with subjective (i.e., survey) data collected through a novel, self-developed e-commerce negotiation platform with an empathic agent. Our results show that the perceived agent's empathic capability positively influences users' trust and satisfaction towards the agent, further impacting their continuous use intention. Notably, users' perceived control over the negotiation moderates the relationship between the perceived empathic capability and trust. This study contributes to the research on automated negotiation agents and empathy, offering practical implications for designing negotiation agents.

Keywords: Negotiation agent; Empathic capability; Trust; Satisfaction; Continuous use intention

1. Introduction

Negotiation is a fundamental process in trading and commerce activities, which involves discussions and exchanges between parties, such as suppliers and purchasers, to reach a compromise or agreement on terms and conditions related to buying and selling goods or services (Al-Jaljouli et al., 2018). However, considering that the engaged parties typically vary in their preferences, interests, and backgrounds, many conflicts may arise during negotiations, rendering the time-consuming process with many phone calls and emails (Shojaiemehr & Rafsanjani, 2018). Thus, according to APQC (American Productivity & Quality Center), the average cycle time for sourcing events can vary from 52 to 74 days or more (Brown, 2020). Previous research suggests that empathy, the ability to perceive, understand, and appropriately respond to others' emotions, thoughts, and behaviors (Murphy et al., 2019), plays a pivotal role in conflict resolution. This is achieved by fostering a deep understanding of diverse perspectives, building trust, and establishing the groundwork for mutually satisfactory agreements.

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[1] Corresponding author.

With the widespread adoption of electronic markets and electronic commerce platforms, an increasing share of trading activities have shifted online (Cheng et al., 2025). This brings advantages such as broader access to trading information, reduced communication costs, and enhanced engagement between buyers and sellers across temporal and spatial barriers (Asante et al., 2023; Fuller et al., 2022). Additionally, incorporating advanced artificial intelligence (AI) technologies into these platforms has propelled the evolution of automated agents beyond providing basic consulting services and transaction data processing, extending into more sophisticated applications for trading activities (Cao et al., 2021). For example, automated agents can now provide tailored consultation feedback and, more recently, have begun to take on the role of negotiators. The negotiation agents are typically designed to provide real-time responses to user inquiries, addressing questions about product details, pricing, and logistics. A notable instance is Pactum[2], an automated negotiation software that helps Walmart and its suppliers streamline negotiations for multiple issues, such as product prices and delivery times. Another example is Echo Global Logistics[3] adopting an automated negotiation system, which can automatically accept, reject, or propose a revised offer once the supplier makes a new offer.

By leveraging AI technologies, agents on digital platforms are increasingly equipped with human-like attributes and capabilities, including automated learning and decision-making, which enable them to communicate with users in a human-like manner (Song et al., 2022). These technological advancements also open up opportunities for the development of AI-enabled empathic agents (Morris et al., 2018; Tsumura & Yamada, 2023). In this context, it means that the agents are able to perceive, understand, and appropriately respond to users' emotions, thoughts, and behaviors. In this study, we focus on AI-enabled empathic agents, i.e., the autonomous software systems capable of delivering timely and accurate responses with minimal human intervention (Saviano et al., 2025), specifically designed to simulate empathic behaviors. By recognizing and responding to users' emotional states, these agents aim to enhance the quality of human-agent interaction and help settle conflicts during negotiations.

On the other hand, it remains unclear whether people treat empathic agents as they would human partners, forming psychological connections (e.g., trust), attitudes (e.g., satisfaction), and behavioral tendencies (e.g., continuous use intention) shaped by social conventions. Unlike human empathy, which arises from genuine emotional experience and is conveyed through cues such as facial expressions and tone, AI empathy is simulated through data-driven models and programmed responses (Saviano et al., 2025). While these systems can mimic empathic interactions, their algorithmic foundations differ fundamentally from the biological and moral basis of human empathy. This distinction raises important questions about how empathic AI agents shape user perceptions and interaction outcomes. The ambiguity is further compounded by the widespread view of AI as a "black box"—unfeeling, uncontrollable, and incapable of delivering predictable results (De Freitas et al., 2023).

The emergence of AI-enabled empathic agents marks a significant shift in the landscape of negotiation research, moving beyond the traditional focus on agent-to-agent interactions to address the complexities of human-to-agent negotiations (Cao et al., 2020; Vahidov et al., 2014). Conceptually, human-to-agent and agent-to-agent negotiations differ fundamentally in the nature of their participants. Human-to-agent negotiation involves direct interaction with humans, requiring agents to recognize and interpret users' emotions and intentions (Cao et al., 2020) and respond appropriately to emotional cues (Kumar et al., 2016; Sinaceur et al., 2015). In contrast, agent-to-agent negotiation is conducted within algorithmic frameworks, where interactions are governed by predefined rules and quantitative parameters. In practical applications, human-to-agent negotiation often leverages algorithms (e.g., BERT) to help agents understand users' emotions, as seen in intelligent customer service systems. Agent-to-agent negotiation, on the other hand, is typically used for large-scale processing of structured transactions, enabling efficient automation in domains such as supply chain management, financial trading, and logistics. Thus, the advancement of AI-enabled empathic agents presents new opportunities to deepen our understanding of human-to-agent negotiations. This involves exploring how users perceive the empathic capabilities of agents and how this perception influences their psychological outcomes and willingness to continue using the agent in future negotiations. Continuous use intention is an important user behavioral intention outcome in information systems and technology implementation (Lv et al., 2025). Therefore, we proposed the following two questions:

(1) How does the user's perception of the agent's empathic capability influence their psychological connections (e.g., trust), attitudes (e.g., satisfaction), and continuous use intention formation?

(2) To what extent does the user's perceived control over the negotiation using the agent influence their continuous use intention?

[2] For a detailed description of Pactum, see: https://pactum.com/

[3] For a detailed description of Echo Global Logistics, see: https://www.echo.com/

To address the research questions, this study developed a model based on social response theory and the literature on empathy. Particularly, social response theory provides a theoretical framework to link users' perceptions of the agent's empathic capability to their psychological outcomes because the empathy expressed by the agent could trigger users' expectations of social responses from the agent. Unlike traditional technologies, empathic agents are expected to exhibit human-like traits, including the ability to recognize and respond to human emotions (Gkinko & Elbanna, 2022). Established adoption theories such as UTAUT (Liang et al., 2024) and TAM (Wong et al., 2023) primarily explain user acceptance through functional factors (e.g., perceived usefulness, ease of use), with limited consideration of emotional aspects. In negotiation contexts, social response theory provides a more appropriate framework, as it explains how users respond to technologies perceived as having social characteristics and how these perceptions influence psychological connections and continuous use intention. This represents a theoretical and practical gap addressed by our study. Moreover, traditional adoption models tend to view technology as static, whereas AI systems like empathic agents possess adaptive learning capabilities that enable them to detect users' emotional states and respond dynamically. Social response theory better accounts for the evolving interaction between users and adaptive technologies in human-to-agent negotiations. Our model is tested and validated with subjective (i.e., survey) data from 203 subjects collected through a self-developed e-commerce negotiation platform equipped with the empathic agent.

Our results show that the users' perception of the agent's empathic capability positively influences their psychological connection (i.e., trust) and satisfaction with the agent, further impacting their willingness to maintain continuous use intention. Notably, users' perceived control over the negotiation moderates their continuous use intention between the perceived empathic capability and trust. This study contributes to the research on automated negotiation agents and empathy, offering practical implications for designing negotiation agents.

2. Conceptual Backgrounds

2.1 Literature Review on Automated Negotiation

The evolution of e-commerce has significantly impacted negotiation practices, namely electronic negotiation, shifting from traditional face-to-face interactions to virtual environments, enabling global reach and 24/7 accessibility. The research of electronic negotiation has progressed through two main stages: negotiation support systems (NSS) and automated negotiation systems (ANS) (Eshragh et al., 2019; Wohlrab & Garlan, 2023). NSS provides fundamental support for online negotiations, such as instant message tools and decision-support suggestions. ANS adopts a negotiation agent, realized by software agent technologies, on behalf of humans to facilitate automated negotiation. Our research on empathic agents falls within this ANS domain.

Automated negotiation systems (ANS) can be classified as human-to-agent or agent-to-agent negotiations, depending on whether a human participant is involved (Türkgeldi et al., 2022). Most studies on agents in negotiation focus primarily on the objective performance outcomes achieved for the parties they represent. These studies (e.g., (Alrayes et al., 2018; Cao et al., 2020; Park et al., 2019; C. Wu et al., 2023)) mainly aim to optimize negotiation success rates, joint utility, or efficiency through strategic or algorithmic enhancements. In the context of human-to-agent negotiations, a growing number of studies have started to consider users' psychological outcomes in using negotiation agents, including satisfaction (Liang et al., 2019; Vahidov et al., 2014) and perceived fairness (Liang et al., 2019; Wu & Sun, 2025). In addition, continuous use intention has emerged as a theoretically meaningful indicator of an agent's effectiveness, particularly in systems designed to simulate socially intelligent behavior. Rather than capturing a one-time outcome, continuous use intention reflects users' willingness to re-engage with an agent (Chou et al., 2010; Lv et al., 2025). Prior work in information systems and human-computer interaction has linked continued use intention to constructs such as trust and satisfaction (Gefen et al., 2003; Venkatesh et al., 2012), suggesting that it serves as an important measure for user–agent interaction outcome. In the case of empathic agents, which aim to foster not only efficient negotiation outcomes but also emotionally resonant interactions, continued use intention offers an integrative measure of both functional and relational effectiveness. Despite its relevance, however, limited research has examined this outcome in the specific context of negotiation agents (Sondern et al., 2025; Wu & Sun, 2025).

This research gap is particularly relevant when considering the distinction between agent-to-agent and human-to-agent negotiations. In agent-to-agent negotiations, human's input is usually absent, and interactions occur within the pre-defined algorithmic frameworks. In contrast, human-to-agent negotiations involve real users, but their inputs are often restricted to price-related information, with little opportunity to express opinions or emotions. Although some research on human-to-agent negotiation has begun incorporating emotions into agent design (e.g., Wu et al. (2024)), emotions are generally treated as functional or technical attributes intended to improve agent performance. In contrast, our study adopts a user-centered perspective, examining how users' perceptions of an agent's empathic capability influence their intention to continue using it. This shifts the focus to the human side of human-to-agent negotiation, emphasizing the counterpart's perspective to assess the agent's impact.

While most ANS research follows a design science approach and emphasizes optimizing system performance through advanced algorithms (Cao et al., 2020; Keskin et al., 2023), it often overlooks how human users perceive these systems in human-to-agent negotiations. In such contexts, users generally have a limited understanding of how the agent operates, including how emotional strategies are implemented. For example, emotional persuasion techniques have been introduced to improve negotiation outcomes (Wu et al., 2024), yet it remains unclear how an agent's emotional expressions influence users' psychological responses. A few studies have attempted to consider users' perceptions by examining the impact of negotiation strategies on outcomes such as perceived usefulness and ease of use (Vahidov et al., 2014; Vahidov et al., 2017). However, these efforts largely treat users' perceptions as secondary conditions and offer limited insight into how users interpret and respond to an agent's empathic capability. Some recent work has begun to explore user-centered outcomes such as trust and satisfaction in response to negotiation agents (Druckman et al., 2021; Park et al., 2019; J. H. Wu et al., 2023), but the role of empathy perception remains underexplored.

In summary, recent research highlights the potential of automated agents with emotion-processing capabilities to enhance negotiation performance in complex human-to-agent negotiations. However, existing systems often limit communication functions for users and lack a user perspective in understanding how empathic agents influence negotiation processes and user outcomes. This hinders our comprehension of the influencing mechanisms of empathic agents in negotiations. To address these gaps, this study investigates how users' perceptions of an empathic agent influence their psychological outcomes and continued use intention, within the context of a novel, self-developed empathic negotiation agent in e-commerce.

2.2 Conceptualization of Negotiation Agent Empathic Capability

Empathy refers to the ability to perceive, understand, and appropriately respond to others' emotions, thoughts, and behaviors (Murphy et al., 2019). It is widely acknowledged as a multidimensional construct comprising cognitive, affective, and behavioral components (Clark et al., 2019). Cognitive empathy involves understanding another person's mental and emotional state by imagining their perspective (Park et al., 2023). Affective empathy is the experience of affective congruence with others, often prompting prosocial motivation and emotional resonance (Mari et al., 2024). Behavioral empathy reflects the outward expression of empathy through verbal or non-verbal behaviors that convey understanding and care. These dimensions collectively contribute to the interpersonal function of empathy, allowing individuals to build emotional connections and engage meaningfully with others.

When applied to negotiation agents, this conceptualization provides a foundation for designing empathic capabilities. As empathic observers, such agents are expected to detect users' emotional expressions and respond in socially appropriate ways. Specifically, an empathic agent should identify emotional cues embedded in users' messages to demonstrate cognitive empathy and interpret them in the context of the ongoing negotiation, which reflects its affective empathy. The agent then conveys behavioral empathy by responding with language and actions that acknowledge and align with the user's emotional state, thereby fostering a sense of understanding and connection. Technically, this is implemented through emotion detection and intent recognition using natural language processing models (e.g., BERT) for cognitive empathy, while affective and behavioral empathy are expressed through predictive modelling and human-like response generation. In this way, an empathic negotiation agent engages with users in a manner that mirrors human empathy, enhancing relational quality and promoting sustained engagement.

While these capabilities are technically implemented as distinct components, users may not evaluate them in isolation. Instead, user perceptions of an agent's empathic capability emerge holistically, based on how well the agent's responses align with their feelings and expectations throughout the interaction. Similar to human-to-human interactions, empathy in human-agent negotiation is inferred from outward expressions, such as timely recognition of emotional states, sensitivity in tone, and responses that feel attuned to the user's situation (Decety & Jackson, 2004; Preston & De Waal, 2002). From the user's perspective, such behavioral signals serve as proxies for empathy, shaping their overall impression of the agent's emotional capabilities. Therefore, this study conceptualizes perceived empathic capability as a unified construct, reflecting users' subjective evaluation of the agent's ability to understand and respond to their emotional states in a negotiation context. This integrative view provides the basis for examining how perceived empathic capability may influence key psychological outcomes, including trust in the agent and the intention to continue engaging with it.

2.3 Social Response Theory

Social response theory posits that individuals perceive computers as social actors, attributing social rules and expectations to them (Nass & Moon, 2000). This phenomenon makes people unconsciously engage with computers using social conventions like politeness (Nass et al., 1999) and reciprocity (Moon, 2000), especially when computers exhibit human-like characteristics and provide social cues (Reeves & Nass, 1996). The roots of this social response lie in the innate human tendency to socialize with others (Nass & Moon, 2000). The impetus for users to engage socially with computers primarily arises from two essential social cues: interaction cues and language cues (Nass &

Steuer, 1993). Interaction cues pertain to the two-way interactive capabilities demonstrated by computers, while language cues encompass the meaningful language used by computers.

By attuning to users' emotions expressed in natural language and responding with appropriate expressions, empathic agents demonstrate both two-way interaction and human-like language cues that foster social engagement. Perspective-taking phrases such as "I understand how that might feel" convey empathy and goodwill. These expressions support the human-to-human negotiation rule of reciprocity, which encourages individuals to respond positively to kind actions and promotes cooperative exchange (Chattaraman et al., 2019; Gouldner, 1960). Similarly, when agents acknowledge users' feelings in a respectful and thoughtful manner, they help create positive, harmonious interactions. This aligns with the rule of politeness, which maintains stable social relationships through considerate behavior (Brown & Levinson, 1987) and is rooted in humans' ability to understand others' thoughts and emotions (Ribino, 2023).

In addition to language cues, empathic agents also use interaction cues, such as timely and consistent follow-ups, to signal attentiveness. These behaviors reinforce users' sense of being heard and recognized, strengthening emotional connection and promoting ongoing engagement. Together, these social cues shape users' perceptions of empathy and guide communication in ways consistent with human-to-human negotiation rules. Behind these cues are the agent's cognitive empathy capabilities, such as emotion detection and intent recognition, as well as affective and behavioral empathy enabled through predictive modeling and human-like responses.

These social cues provided by empathic agents not only facilitate communication aligned with human-to-human negotiation rules, but also shape users' cognitive processing during decision-making. Users' expectations and reliance on the automated agent's social responses in the interaction may also stem from their inclination to avoid detailed information processing. Instead, they focus on social cues, such as the agent's tones or emotions, to form heuristics for making judgments (Chaiken, 1980). Building on Dula et al. (2024), heightened emotional and social responses to automated agents may foster greater trust. Similarly, Chen et al. (2021) suggested that automated agents, which provide users with friendly communication, make consumers feel the fit between the presented information and the shopping task decision. These theoretical foundations collectively underscore the unique role of empathy beyond basic sociability in human-agent interactions. In our context, this suggests that users may interpret negotiation messages differently when agents exhibit empathic capabilities. These capabilities are conveyed through specific interaction styles and linguistic cues that signal empathy. Rather than focusing solely on the content of the offer, users also respond to the emotional feedback embedded in the agent's communication style.

In sum, we posit that agents' empathic capability is pivotal in shaping users' perceptions and expectations towards the agents. Specifically, when confronted with users experiencing negative emotions, an automated agent that fails to capture and respond to these emotions may exacerbate users' negative feelings and lead to users' irritation. Conversely, users may engage positively with empathic agents, viewing them as social entities and negotiating politely and reciprocally. The compliance with these social conventions is crucial for negotiators to resolve conflicts, establish deals efficiently and effectively, and lay the foundations for business relationships.

3. Hypotheses Development

The research model is developed based on social response theory and the literature on empathy, as shown in Figure 1. Specifically, the users' *perceived empathic capability of the agent* refers to the extent to which the users believe that the agent is capable of understanding their emotions, which would serve as the foundation for the agent to respond to them with social appropriateness. This perception reflects the agent's warmth, compassion, and care towards the users.

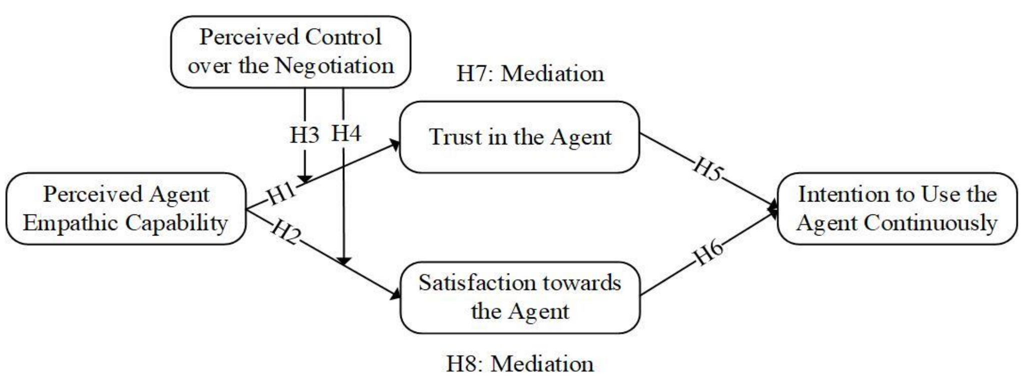

Figure 1. Research Model

Trust signifies a profound psychological bond that is not only built on the benevolence exhibited by the trustee (i.e., the agent in our case) but also influenced by the trustee's adherence to the acceptable principles of the trustor (i.e., the human user) (Murphy et al., 2019). Satisfaction is the disparity between a user's cognition during the negotiation process and initial expectations when engaging with an agent (Rolph E, 1973). We postulate that the effect of the users' perceived empathic capability of the agent on their trust and satisfaction can be further impacted by their conviction that the agent can operate in a transparent and manageable manner. Therefore, users' perceived control over the negotiation is included as a moderator in the relationship between their perceived empathic capability, trust, and satisfaction. Below, we elaborate on each hypothesis.

Trust refers to the sense of security rooted in the belief or expectation that the counterpart will deliver benefits rather than inflict harm (Mayer et al., 1995). When negotiating with the agent, users' trust indicates their assurance built upon the belief or expectation that the agent will act in their best interests. More specifically, this could be demonstrated by the agents' capability to promptly respond to users' needs and assist them in making decisions (Murphy et al., 2019). Since empathy is a prerequisite for building trust between individuals (Huang & Lin, 2011), we posit that the users' perceived empathy from the agent is also important for them to build trust in the agent. Specifically, social response theory explains that people tend to treat computers as social actors when these systems exhibit human-like social behaviors. Therefore, when an agent shows empathy and responds sensitively to users' needs, users are more likely to perceive it as a genuine social counterpart. This could foster a perception that the agent is reliable (Han & Yang, 2018) and willing to make concessions for users' interests (Sullivan et al., 2022). In this sense, their trust in the agent could increase. Therefore, we hypothesize:

H1. *The user-perceived agent's empathic capability has a positive effect on the user's trust in the agent.*

In addition to trust, the extent to which users believe the agent possesses empathic capability can also influence their satisfaction with the agent. In traditional negotiation contexts, empathy has been shown to strengthen the relational bond between customers and service providers (Van den Broeck et al., 2019) and improve customer satisfaction (Ndubisi & Nataraajan, 2018). According to social response theory, individuals tend to apply social norms and interpersonal expectations when interacting with media that exhibit human-like cues, such as empathic language (Huang & Lin, 2011). When users perceive an agent's responses as empathic, they are likely to interpret the interaction as socially reciprocal, which may lead them to view the agent as beneficial, thereby increasing their satisfaction. Additionally, empathic expressions can help regulate users' negative emotions—such as confusion, anxiety, or frustration—thus improving their evaluation of the interaction. As Gursoy et al. (2019) suggest, users tend to feel more satisfied with information systems that respond appropriately to emotional needs. Therefore, we hypothesize that:

H2. The user-perceived agent's empathic capability has a positive impact on the user's satisfaction with the agent.

Individuals' perceptions of control reflect their subjective belief in their ability to influence or manage a situation or outcome (Skinner, 1996). Accordingly, we define users' perceived control over the negotiation as their belief in their ability to influence or manage the negotiation process and its outcomes when interacting with the agent. According to social response theory, users' belief in an agent's empathic capability can lead them to form social expectations toward the agent. We argue that perceived control further shapes both the development of these expectations and users' beliefs about the extent to which the agent meets their expectations.

Specifically, users with high perceived control believe they can make independent decisions and steer the negotiation toward their desired outcomes. As a result, they are more likely to perceive that the empathic agent recognizes and supports their goal of maximizing benefits and the social norms (e.g., reciprocity). This perception can reduce the sense of threat that might otherwise arise from interacting with an intelligent yet complex agent (Schmuck & von Sikorski, 2020), and can encourage users to form a connection with the agent, thereby increasing the likelihood of trust (Wixom & Todd, 2005; Murphy et al., 2019). Similarly, when users perceive a high level of control over the negotiation process, the reduced uncertainty they experience, such as from unexpected offers provided by the agent, can reinforce the impression that the agent follows social norms and acts in their best interest, thereby fostering a more positive attitude (i.e., satisfaction, in our case) toward the agent.

Conversely, when users perceive low control over the negotiation, the agent's empathic behavior may appear less trustworthy and be associated with more negative attitudes. Without a sense of control, users may question whether the agent's empathy genuinely serves their interests, for example, by helping them achieve a favorable price. In such cases, users may focus more on potentially threatening cues related to risk, competition, and pricing. This heightened sensitivity can lead them to adopt a defensive stance toward the agent as a form of self-protection, which may hinder the formation of trust and satisfaction. Therefore, we hypothesize that:

H3. The user-perceived control over the negotiation enhances the positive effect of their perceived agent's empathic capability on trust. Specifically, when user perceived control over negotiation is high, the positive effect of their perceived agent's empathic capability on trust is stronger than when it is low.

H4. *The user-perceived control over the negotiation enhances the positive effect of their perceived agent's empathic capability on satisfaction. Specifically, when user perceived control over negotiation is high, the positive effect of their perceived agent's empathic capability on satisfaction is stronger than when it is low.*

According to Bhattacherjee (2001), continuous use intention refers to users' willingness to engage with the empathic agent in future negotiations. A key factor influencing this intention can be users' trust in AI technologies, which plays a critical role in sustaining their continued engagement (Ventre, 2020). Social response theory suggests that users expect computers to follow social norms, which shapes how they communicate and interact with such systems. When users perceive the agent as empathic and trustworthy, they feel socially connected to it and confident that it will meet their expectations during negotiations (Murphy et al., 2019; Nass & Moon, 2000). Moreover, Liu (2021) further demonstrates that users' perception of a stable connection with the AI agent, indicating their belief that the AI will behave consistently and cooperatively during the interaction, significantly enhances their continuous use intention. Accordingly, when users believe that an AI-enabled empathic agent can effectively serve their interests, they are more likely to continue using it in future negotiations (McNeese et al., 2021). Conversely, a breakdown of trust during negotiation may reduce users' willingness to engage with the agent again.

Also, satisfaction is a key factor influencing users' intention to continuously use information technologies (Li et al., 2023; Zhou et al., 2024). As previously discussed through the lens of social response theory, satisfaction arises when an agent's empathic capabilities meet users' social expectations (Cheng et al., 2021). This satisfaction can, in turn, strengthen users' engagement with the agent. When users perceive their negotiation experience with the agent as satisfactory, they are more likely to engage in future interactions. Accordingly, we hypothesize that:

H5. *The users' trust in the agent has a positive effect on their intention to use it continuously.*

H6. *The users' satisfaction with the agent has a positive effect on their intention to use it continuously.*

H7. *The users' trust mediates the effect of user-perceived agent's empathic capability and their intention to use it continuously.*

H8. *The users' satisfaction mediates the effect of user-perceived agent's empathic capability and their intention to use it continuously.*

4. Methodology

4.1 Research Context

We conducted a scenario-based survey to test our hypotheses in the self-developed automated negotiation system, EasyNego, equipped with an empathic agent. The development of the empathic agent complies with the design science paradigm (Ahmad et al., 2022). According to the conceptualization of the negotiation agent's empathic capability, cognitive empathy describes the agent's ability to track the target's internal states or detect the target's feelings, affective empathy involves the agent's capability to understand the target's intentions, beliefs, and emotions and behavioral empathy means the agent makes a corresponding text response to the user's emotion. To realize cognitive empathy, the empathic agent is designed to be able to detect the user's emotions, which are delivered through natural language, based on the BERT model[4,5] (Zhao et al., 2022). Additionally, to realize affective and behavioral empathy, this agent also possesses the capability of predicting users' expectations on price by inferring from their emotions. Furthermore, the agent is also designed to predict the user's future offer trends by using the artificial neural network technique, judge the user's offer pattern (e.g., competitive, collaborative, or neutral) by using the Bayesian learning technique, depict the user's future offer track by using the segmented nonlinear regression technique, and make the counteroffer by using the reinforcement learning technique. Thus, the agent can respond to the user's offer by making emotionally attuned counteroffers.

Specifically, the EasyNego system comprises front-end and back-end systems, as shown in Figure 2. The front-end system supports the communication between the negotiation agent and the human user. It features a chat box (see Figure 3) where users can respond to the agent's offers and make counteroffers, just as we use WhatsApp or WeChat to chat online. After a user inputs messages in the chat box, the back-end system would process the messages and generate responses to be sent back to the user. During the negotiation, users can accept or reject offers directly by

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[4] Bidirectional Encoder Representations from Transformers (BERT) is a pre-trained language model on the large-scale corpus. BERT model effectively uses Chinese information. By comparing BERT with other text pre-training models (e.g. Word2vec), this paper finds that BERT has the best accuracy and precision.

[5] For a detailed description of BERT, see: https://github.com/USjeje/chinese_L-12_H-768_A-12/tree/main.

clicking the buttons in the chat box, signaling to conclude the negotiation process and halt the operations of the back-end system.

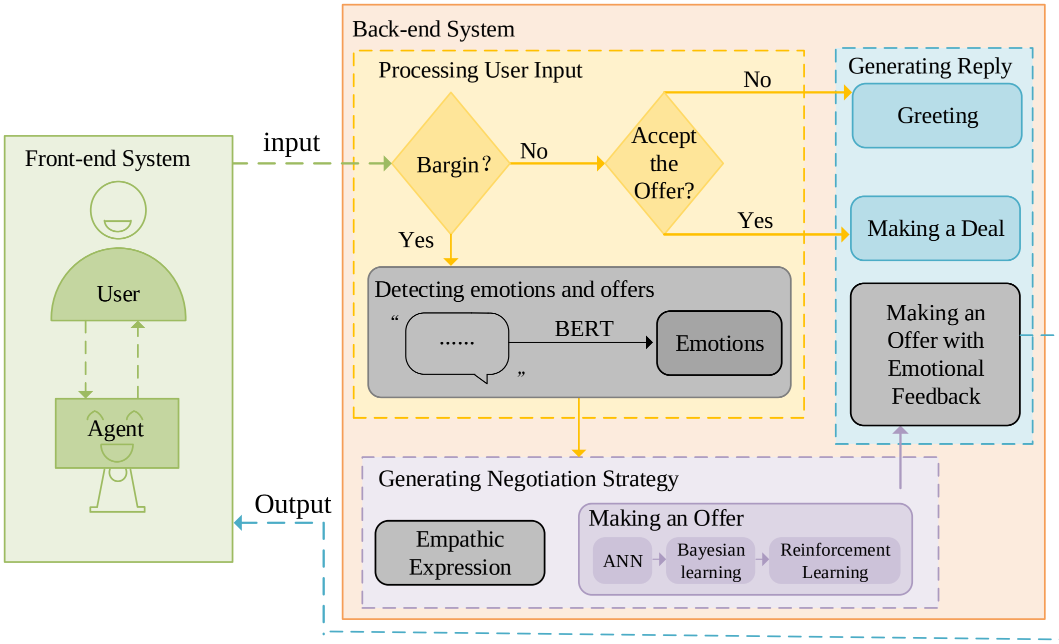

Figure 2. AI-Enabled Negotiation System Framework of EasyNego

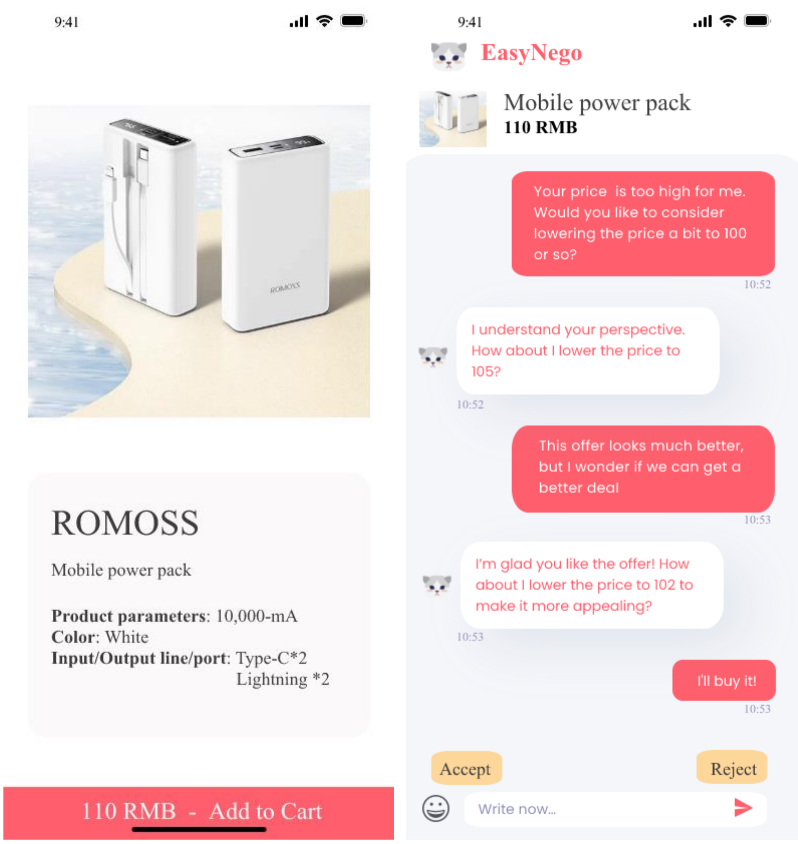

Figure 3. The Front-end System Interface of EasyNego

As the basis to enable the empathic agent, the back-end system initially assesses whether the user has the intention to bargain. If the user intends to bargain by offering a new price and says, for example, "*Your price [RMB 110] is too high for me. Would you like to consider lowering the price a bit to 100 or so?*", the agent will detect the emotional expressions and identify the user's offer based on the BERT technique. Such information then serves as the input for the negotiation strategy generation module. This module generates a counteroffer to the user's proposed price based on multiple machine-learning techniques and proposes emotional expressions, both of which contribute to the agent's responses to the user.

For instance, in the abovementioned case, the agent could interpret the dissatisfaction from the user with the previously offered price and hence will try to address the concern, saying, "*I understand your perspective. Let's explore options to adjust the price and make it more affordable. How about I lower the price to 105?*". On the contrary, if the user expresses contentment with the proposed offer while still expressing a bargain intent by saying, "*This offer looks much better, but I wonder if we can get a better deal?*", the agent could be stimulated to enthusiastically respond, saying, "*I'm glad you like the offer! How about I lower the price to 102 to make it more appealing?*"

On the other hand, if the agent initially identifies that the user does not intend to bargain by saying, for example, "*I'll buy it"* or "*I don't think I would accept your offer*", or directly clicking the decision buttons, the agent will further check whether or not the user accepts the offer or rejects the offer. If the user accepts the offer, a message is sent indicating the deal has been made, and if the user rejects the offer, a greeting response is sent. The negotiation process continues until a user decision is made, or it will be forcibly terminated due to the round limit.

4.2 Research Procedure

Our scenario-based survey is conducted based on the assumption that the agent enabled by the EasyNego system possesses empathic capability. To validate this assumption, we devised an experimental pre-test to evaluate the agent's empathic capability as shown in Appendix A.

In the formal procedure, we recruited 235 participants by posting invitations on social media (e.g., QQ and WeChat groups) and distributing leaflets at a university. We adopt the negotiation reward structure of Cao et al. (2020) to encourage participants to take the negotiation task seriously and to simulate real-world price sensitivity. A base reward of 8 RMB was offered to ensure participation regardless of negotiation outcomes, while additional gifts (ranging from 10 to 50 RMB) were used to minimize monetary priming effects[6]. They were asked to complete a standard informed consent form to join the study. Once the study began, participants were guided to perform a simulated shopping task (see Appendix B), where they needed to negotiate the product price with the agent enabled by the EasyNego system and finish a survey.

Specifically, participants were initially prompted to imagine that a discount season was approaching when they wanted to buy a 10,000-mA mobile power pack. Subsequently, participants were presented with an instructional training video for using the EasyNego system, and they needed to complete the attention test before logging in to the system, ensuring they understood the use of the negotiation platform and the task. This training video was applied to help the participants learn how to start, continue, and end the negotiation with the agent. It also shows the common commands for giving or making a deal. For example, they could say "Hello" to start to initiate the negotiation process with the agent, they could give a clear offer by saying "100 is a pretty good price", and they could also directly accept or reject the deal provided by the agent by clicking the buttons (as depicted in Figure 3) in the interface.

Once they passed the attention check, they were directed to log in to the EasyNego system through the browser on their mobile phones/iPads/computers to begin the negotiation process for purchasing a product, a mobile power pack initially priced at 110 RMB. At the end of the negotiation process, participants were automatically redirected to finish the survey according to their negotiation experience with the agent.

4.3 Variables and Measures

We have adapted our measures from previous studies based on their definitions, i.e., trust in the agent, satisfaction with the agent, and intention to use the agent continuously. In addition, we have also developed items to measure users' perceived empathic capability of agents and perceived control over the negotiation based on prior literature. These constructs, measures, and their sources are shown in Table 1. All these constructs were reflective and measured with the 7-point Likert scale anchored from "strongly disagree" to "strongly agree".

For control variables, we measured participants' age, gender, education, occupation, average monthly expenses, and online shopping tenure (Losh, 2004; Song et al., 2022).

[6] Participants who obtain a lower deal price earn additional gift rewards: in the top 10 percentile, in the top 10–20 percentile, and in the top 20–30 percentile of the participants receive an additional gift worth 50, 30, and 10 RMB. respectively.

Table 1. Constructs and Measures

Constructs	Items	Sources
Perceived Agent Empathic Capability (PEC)	PEC1: The agent can often understand how I feel. PEC2: The agent is able to recognize promptly when I am upset. PEC3: The agent can get caught up in my feelings easily.	Adapted from Song et al. (2022)
Trust in the Agent (TRU)	TRU1: 1 I believe the agent is sincere and genuine. TRU2: I trust that my information remains secure during negotiations with the agent. TRU3: I have confidence that the agent consistently acts in alignment with my best interests.	Adapted from Venkatesh et al. (2016) and Pelau et al. (2021)
Satisfaction towards the Agent (SAT)	SAT1: I am quite pleased with using the agent. SAT2: Overall, I am very satisfied with my interaction with the agent. SAT3: I feel that my overall experience with the agent is very satisfactory.	Adapted from Wixom and Todd (2005) and Bhattacherjee (2001)
Perceived Control over the Negotiation (PCN)	PCN1: If I wanted to, I could easily control the price offered by the agent. PCN2: I believe that I can control the negotiation consequences. PCN3: I am in the control of the majority of negotiation proceedings. PCN4: I possess considerable control over my actions and their timing during the negotiation with the agent.	Adapted from Consiglio et al. (2018) and Grewal et al. (2007)
Intention to Continuously Use the Agent (CUI)	CUI1: I plan to continue using the agent in the future. CUI2: I expect my use of the agent to continue in the future. CUI3: I intend to continue using the agent in the future.	Adapted from Agarwal and Karahanna (2000)

4.4 Sample Description

Originally, we had 235 participants who joined our study and finished the scenario-based survey. To ensure the quality of the data, we have dropped the samples who failed to correctly respond to the attention test (N=18). Subsequently, we have also dropped the samples who failed to make a deal (N=14). Among them, 9 reached the maximum number of negotiation rounds without making a deal, while 5 finally rejected the offer provided by the negotiation agent and ended the negotiation. We excluded this group of participants, as we assume that deal completion may involve different underlying mechanisms beyond the scope of our current model. To assess whether this exclusion may introduce selection bias, we conducted independent samples t-tests comparing those who completed a deal with those who did not. The results showed no significant differences in demographics or perceptions of the agent's empathic capability[7]. In addition, we employed a logit model to assess whether perceived empathic capability influences the decision to reach a deal. The results show that the agent's empathic capability does not influence deal completion (β of PEC = 0.099; p = 0.787 > 0.05). In this sense, whether or not the participants reach a deal could be influenced by different factors in terms of users' perception of the agent. These results suggest that the exclusion of non-deal participants is unlikely to introduce selection bias into our analysis. In sum, we include 203 responses in our data analysis. The demographics of the final sample are presented in Table 2.

[7] The results showed no significant differences in age (p = 0.627), gender (p = 0.160), education (p = 0.355), average monthly consumption (p = 0.280), or tenure of online shopping (p = 0.108). Perceived empathic capability also did not differ significantly (p = 0.752).

Table 2. Demographics of the Final Sample

Characteristics	Level	Frequency	%
Age	<=18	8	3.94
	19-24	144	70.94
	26-30	42	20.69
	31-35	7	3.45
	>=36	2	0.99
Gender (GEN)	Female	106	52.22
	Male	97	47.78
Education (EDU)	Highschool	2	0.99
	Bachelor	124	61.08
	Master	67	33.00
	Doctor	10	4.93
Occupation (OCC)	Student	189	93.10
	Employees of Government or Institutions	6	2.96
	Company Employee	5	2.46
	Individual Industrial Entity	1	0.49
	Other	2	0.99
Average Monthly Expenses (AME, RMB)	<1500	26	12.81
	1500-3000	133	65.52
	3000-5000	38	18.72
	5000-7000	4	1.97
	>7000	2	0.99
Tenure of Online Shopping (TOS, Year)	<1	2	0.99
	1-2	20	9.85
	2-3	14	6.90
	>3	167	82.27

5 Results

5.1 Instrument Validation and Descriptive Analysis

To validate our instrument, we assessed its convergent and discriminant validity and reliability (MacKenzie et al., 2011). Specifically, we ran exploratory factor analysis (EFA) to assess convergent and discriminant validity. The result is shown in Table 3. As can be seen, each item's factor loading on its intended construct was larger than 0.5 in the EFA (Hair et al., 2013), and the average variance extracted (AVE) of each construct exceeded 0.5, providing evidence of convergent validity. Discriminant validity was demonstrated by the fact that items did not cross-load on other constructs, and the square root of the AVE was higher than the inter-construct correlations (MacKenzie et al., 2011), as shown in the diagonal elements of Table 4. The reliability was assessed by Cronbach's α (CA>0.7) and composite reliability (CR>0.7). As can be seen in Table 4, the CA and CR for all reflective constructs satisfy the thresholds.

Table 3. Exploratory Factor Analysis

	1	2	3	4	5
PEC1	0.05	0.00	0.44	0.23	**0.65**
PEC2	0.13	0.13	0.11	0.14	**0.84**
PEC3	0.06	0.15	0.01	0.45	**0.62**
TRU1	0.18	0.16	0.09	**0.71**	0.41
TRU2	0.10	0.38	0.41	**0.67**	0.06
TRU3	0.13	0.14	0.24	**0.78**	0.30
SAT1	0.10	0.23	**0.82**	0.23	0.09
SAT2	0.15	0.45	**0.64**	0.15	0.34
SAT3	0.17	0.57	**0.61**	0.18	0.20
CUI1	0.02	**0.85**	0.21	0.22	0.21
CUI2	0.22	**0.81**	0.27	0.24	0.05
CUI3	0.15	**0.81**	0.37	0.18	0.11

PCN1	**0.85**	0.09	0.19	0.11	0.09
PCN2	**0.88**	0.05	0.12	0.13	0.03
PCN3	**0.88**	0.13	0.05	0.05	0.19
PCN4	**0.81**	0.19	0.09	0.23	0.11
%Variance	44.59	14.48	9.92	4.65	4.15
Cumulative%	44.59	59.07	68.99	73.64	77.79

At the same time, the correlation coefficient of each variable is shown in Table 4. Furthermore, multicollinearity was also not a concern as the variance inflation factors (VIFs in Table 4) were below the recommended ceiling of 5 (i.e., the VIF of these constructs ranged from 1.05 to 2.77) (Diamantopoulos & Siguaw, 2006). Finally, since we employed a single data collection method for the independent and the dependent variables, we tested for common method bias among them (Podsakoff et al., 2003). Specifically, we employed the marker variable technique and took the smallest correlation between the constructs and the marker variable as the common method variance (Lindell & Whitney, 2001; Richardson et al., 2009). After partialling out the common method variance, the changes in the correlations between our interest constructs are minimal (below 10%), with no impact on the original significance levels (see Table C1 and C2 in Appendix C). Moreover, we also followed Liang et al. (2007) to include a method factor in our measurement model. The average substantive variance of the indicators explained is 0.758, while the average method-based variance is 0.004 (see Table C3). Both test results imply that the common method bias may not be a concern.

Table 4. Correlations, Mean, Std. Dev, VIF, CA and CR

	PEC	TRU	SAT	CUI	PCN	GEN	AGE	EDU	OCC	AME	TOS
PEC	0.64										
TRU	0.65***	0.73									
SAT	0.52***	0.61***	0.78								
CUI	0.39***	0.57***	0.74***	0.86							
PCN	0.29***	0.38***	0.37***	0.34***	0.78						
GEN	-0.06	0.02	0.06	0.02	0.02	-					
AGE	-0.09	-0.12 *	-0.18**	-0.18**	-0.04	0.12	-				
EDU	-0.07	-0.11	-0.25***	-0.24***	-0.20***	0.00	0.23***	-			
OCC	-0.03	-0.07	0.05	-0.021	-0.10	-0.13	-0.14	0.04	-		
AME	0.07	0.03	-0.05	-0.06	0.05	0.10	0.10	-0.01	-0.17*	-	
TOS	0.11	0.03	-0.09	-0.10	-0.08	0.12*	0.08	0.30***	0.11	0.08	-
Mean	5.10	4.97	4.98	4.74	5.17	NA	NA	NA	NA	NA	NA
Std. Dev	1.00	1.18	1.30	1.43	1.09	NA	NA	NA	NA	NA	NA
VIF	1.91	2.33	2.77	2.40	1.26	1.08	1.12	1.25	1.08	1.05	1.17
CA	0.72	0.82	0.86	0.92	0.91	-	-	-	-	-	-
CR	0.84	0.89	0.91	0.95	0.93	-	-	-	-	-	-

Notes: ***p<0.001, **p<0.01, *p<0.05; Diagonal elements are the square root of average extracted (AVE); PEC=Perceived Agent Empathic Capability, TRU=Trust, SAT=Satisfaction, CUI=Continuous Use Intention, PCN=Perceived Control over the Negotiation, GEN=Gender, EDU=Education, OCC=Occupation, AME=Average Monthly Expenses, and TOS=Tenure of Online Shopping; Gender, age, education, occupation, average monthly expenses and tenure of online shopping are categories variables (see Table 2), hence mean are NA; - indicates that CA and CR are NA because construct has a single measure.

5.2 Hypotheses Testing

We used linear regression with ordinary least squares (OLS) to test the hypotheses, because of its relative robustness to deviations from a multivariate distribution (Goodhue et al., 2012). Table 5 shows the results of the hypotheses testing[8]. There are four models. Model 1 examines trust as the dependent variable, while Model 2 focuses on satisfaction. Models 3a and 3b address continuous use intention as the dependent variable, with Model 3a representing the control model and Model 3b the full model. As can be seen, perceived agent empathic capability is found to positively influence users' trust in the agent (β = 0.71; p < 0.001) and their satisfaction towards the agent (β = 0.61; p < 0.001). Therefore, H1 and H2 are supported. Moreover, as hypothesized, users' perceived control over the negotiation positively moderates the relationship between perceived agent empathic capability and their trust in the agent (β = 0.14; p < 0.01), supporting H3. Last, users' trust (β = 0.28; p < 0.001) and satisfaction (β = 0.68; p < 0.001) towards the agent show significant and positive effects on their intention to use the agent continuously. Thus, H5 and H6 were supported. We found out that H4 is not supported. This indicates that the empathic capacity has a direct effect on users' satisfaction and the perceived control has no impact on this relationship.

Table 5. The Results of Hypotheses Testing

	Model 1: DV=Trust	**Hypo.**	**Model 2: DV=Satisfaction**	**Hypo.**
Controls				
Age	-0.13 (0.13)	-	-0.20 (0.17)	-
Gender	0.13 (0.12)	-	0.26 (0.15)	-
Education	0.01 (0.11)	-	-0.28 (0.16)	-
Average Monthly Consumption	0.01 (0.10)	-	-0.10 (0.09)	-
Occupation	-0.10 (0.33)	-	0.48 (0.33)	-
Tenure of Online Shopping	0.03 (0.09)	-	-0.05 (0.11)	
Main Effects				
Perceived Agent Empathic Capability	0.66*** (0.07)	H1 supported	0.51*** (0.09)	H2 supported
Perceived Control over the Negotiation	0.32*** (0.07)	-	0.33*** (0.10)	-
Perceived Agent Empathic Capability× Perceived Control over the Negotiation	0.17** (0.05)	H3 supported	0.11 (0.06)	H4 not supported
R^2	0.48	-	0.35	-
	Model 3a – Control: DV=Continuous Use Intention	**Hypo.**	**Model 3b - Full: DV=Continuous Use Intention**	**Hypo.**
Controls				
Age	-0.27 (0.20)		-0.10 (0.10)	-
Gender	0.18 (0.19)		-0.07 (0.14)	-
Education	-0.31 (0.16)		-0.10 (0.10)	-
Average Monthly Consumption	-0.12 (0.13)		-0.05 (0.09)	-
Occupation	-0.16 (0.38)		0.20 (0.12)	-
Tenure of Online Shopping	-0.12 (0.14)		-0.06 (0.12)	-
Perceived Empathic Capability	0.48*** (0.09)		-0.13 (0.09)	
Main Effects				-
Trust in the Agent			0.28*** (0.09)	H5 supported

[8] We also conducted a robustness check by including the previously excluded participants who did not reach a deal, as clarified in the sample description. The results remain consistent with our main findings in Table 5.

Satisfaction towards the Agent			0.68*** (0.07)	H6 supported
R^2	0.20	-	0.58	

Note: ***p<0.001*, **p<0.01, * p<0.05.
Robust standard errors are in brackets.
PEC and PCN were mean-centered before generating the interaction term.

Furthermore, we have conducted mediation and moderated mediation tests on the effects of trust, satisfaction and perceived control. Specifically, we utilized the bootstrapping method with 5000 repetitions to construct confidence intervals (CIs) (Edwards & Lambert, 2007; Hayes, 2009). Table 6 presents the bootstrapping results along with the corresponding 95% CIs. It shows that users' trust and satisfaction towards the agent mediate the relationship between the perceived agent's empathic capability and their intention to use the agent continuously. At the same time, user-perceived control over the negotiation enhances the positive effect of their perceived agent's empathic capability on trust.

Table 6. Results of Moderated Mediation Tests for Trust and Satisfaction

Relationship	**Moderator (PCN)**	**Direct Effect**	**Indirect Effect**	**95% Bias-Corrected CI**		**Results**	**Hypo.**
				Lower Bound	**Upper Bound**		
PEC->TRU->CUI	High	-0.090	0.189	0.350	0.630	Full mediation	H7 supported
	Low			0.653	0.947		
PEC->SAT->CUI			0.383	0.259	0.507	Full mediation	H8 supported

6 Discussions

Based on social response theory and the literature on empathy, this study suggests that perceived agent empathic capability significantly improves the negotiation user's continuous use intention. Specifically, our study shows that users' trust and satisfaction towards the agent mediate the positive relationship between perceived agent empathic capability and their intention to use the agent continuously. Additionally, the higher the users' perceived control over the negotiation, the stronger the influence of perceived agent empathic capability on trust.

However, we fail to find the significant role of perceived control in moderating the relationship between empathic capability and satisfaction. This may be because of the difference between trust and satisfaction. Trust represents a psychological state depending on relation-based evaluation (Nicholson et al., 2001). In this sense, users with higher perceived control develop stronger confidence in their ability to influence this reciprocal relationship. In contrast, satisfaction reflects users' assessment of whether the agent's demonstrated value aligns with user expectations, essentially a judgment of functional utility (Najjar et al., 2016). The perception of empathic capability directly fulfills users' fundamental expectation that the agent understands their needs. Crucially, such evaluation is primarily determined by users' perception of the agent's empathic capability rather than by their sense of control.

6.1 Theoretical Contributions

This study contributes to the literature on negotiation agents, social response theory, and empathy. First, this study extends the automated negotiation literature by shifting the focus from optimizing agent performance to examining its impact from the human counterpart's perspective. Complementing the emerging work on negotiation agents that take into account the human counterpart's emotions into system design (Wu et al., 2024), this study delves into the mechanisms of an agent equipped with empathic capabilities in influencing their human counterpart's (or user's) psychological outcomes by assessing their perceptions. Particularly, our study reveals that users' perceived agent empathic capability can foster their trust and satisfaction, which further motivates them to form intentions for future interactions with the agent.

Second, this study contributes to the literature on empathy by contextualizing it within AI-enabled negotiation. It offers a conceptual foundation for designing empathic agents grounded in cognitive, affective, and behavioral dimensions of empathy. This approach broadens the understanding of empathy in human-to-information system, human-to-agent, and human-to-AI interactions. Notably, in the context of human-to-agent negotiation, the study highlights that the effect of an agent's empathic capability on users' continuous use intention is moderated by users' perceived control over the negotiation process.

Last but not least, this study contributes to the literature on social response theory by applying it to AI-enabled automated negotiation. It demonstrates that when an agent exhibits empathic cues, users may respond as if they are interacting with a socially present, human-like counterpart. This is evidenced by the significant influence of perceived agent empathic capability on users' trust, satisfaction, and continuous use intention. These findings support the idea that users not only recognize social behaviors in AI agents but also form meaningful evaluations and continuous interactions based on those perceptions.

6.2 Managerial Implications

With the advancement of AI technologies, automated agents have been increasingly utilized in various aspects of e-commerce, including negotiations studied in this research. Our study findings offer valuable suggestions to the designers of negotiation agents and the companies incorporating such technology. First, e-commerce companies that embrace AI technologies for automated agents could prioritize integrating empathy into their negotiation agents. For instance, they might develop agents capable of understanding and responding to customer emotions during negotiations, leading to more successful deals. Our research indicates that high user perception of the empathic capabilities can greatly foster stronger customer relationships.

In addition, to promote the users' acceptance and use of the negotiation agents, designers could incorporate advanced AI techniques to improve the agents' capability in emotional detection and inference. For example, incorporating a mature language model (e.g., BERT as employed in our study, or other LLM technologies) to interpret natural language in specific contexts may contribute to more stable and accurate outputs (Zhen et al., 2023). Such models are capable of better identifying emotional cues in text while reducing the risk of over-interpretation. This capability could be particularly beneficial for negotiation agents, where understanding users' emotions and intentions with greater accuracy may help in tailoring responses to different emotional states. In turn, this might support strategies that are more aligned with users' needs and expectations, potentially enhancing their overall negotiation experience.

Furthermore, as users' perceived control over negotiation amplifies the impact of the agent's empathic capability on users' trust, designers can adjust the agent's language and interactive interface to reinforce users' belief in dominating the negotiation process and consequences. For instance, using phrases like "you have the final say" could emphasize users' autonomy and empower them. At the same time, visual elements like progress bars may enhance their sense of involvement in the process. Personalized negotiation strategies aligning with users' preferences could strengthen their confidence in negotiation consequences. Tailoring language and interface design to enhance users' perceptions of control allows designers to effectively leverage empathic capability for building trust and engagement in negotiations.

6.3 Limitations and Future Research

The findings of this study should be interpreted in light of several limitations. First, while student samples are commonly used and generally considered appropriate in this research context (Koo, 2016; Micu & Chowdhury, 2010; Royne, 2008), we acknowledge the limited diversity in our sample, particularly with respect to income levels. Future research could examine how income levels influence human-to-agent negotiation behavior, with attention to potential differences in price sensitivity, risk preferences, and concession strategies across demographic segments.

Second, while this study focuses on the agent's empathic capability and its impact on relational outcomes, it does not address potential ethical concerns associated with embedding anthropopathic features in automated agents, such as issues of fairness and integrity. Future research could explore how to balance the design of socially engaging agents with ethical considerations. Moreover, our study's investigation of psychological mechanisms is limited, and hence future work could identify additional mediators linking empathic capability to user trust and satisfaction. Studies might also vary technical design elements to assess how different levels or types of empathic capability affect user psychology and behavior, particularly from a design science perspective and across different boundary conditions.

Third, while the study is situated in an e-commerce context, the insights may extend to other domains involving prolonged negotiation processes. Future research could thus apply and validate the model in areas such as automated recruitment platforms, human resource negotiations, or gaming environments involving non-player characters.

Fourth, while this study aimed to simulate a naturalistic negotiation setting, it did not systematically examine the effects of contextual cues such as discount framing. Future research could manipulate price-related cues (e.g., original vs. discounted prices) to explore how these factors shape user perceptions of offers and negotiation behavior. At the same time, we recognize the importance of simulating realistic e-commerce negotiation scenarios and capturing actual user behavior over time to enhance the ecological validity of our findings. Such efforts would provide valuable insights into how users interact with empathic agents in authentic decision-making contexts and the behavioral outcomes that result.

7 Conclusions

Considering the lack of understanding of the negotiation between humans and empathic agents, the study developed a model based on social response theory and the literature on empathy to assess the impact of user-perceived agent empathic capability on negotiation relational outcomes. By conducting a scenario-based survey using a self-developed AI negotiation system, this study finds that users perceived empathic capability of the agent significantly enhances their intention to continue using the agent, mediated by increased trust and satisfaction. Furthermore, users' perceived control over the negotiation positively moderates the relationship between perceived empathic capability and trust. These findings contribute to the literature on automated negotiation agents and empathy, and offer practical insights for designing negotiation agents that foster sustained user engagement.

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APPENDIXES

Appendix A Pre-test of the Empathic Capability of EasyNego

Aligning with the structure of our formal study, we crafted a scenario in which participants are asked to purchase a stainless-steel thermos cup with 500ml capacity, initially priced at 115 RMB. The negotiation interface of EasyNego is shown in Figure A1.

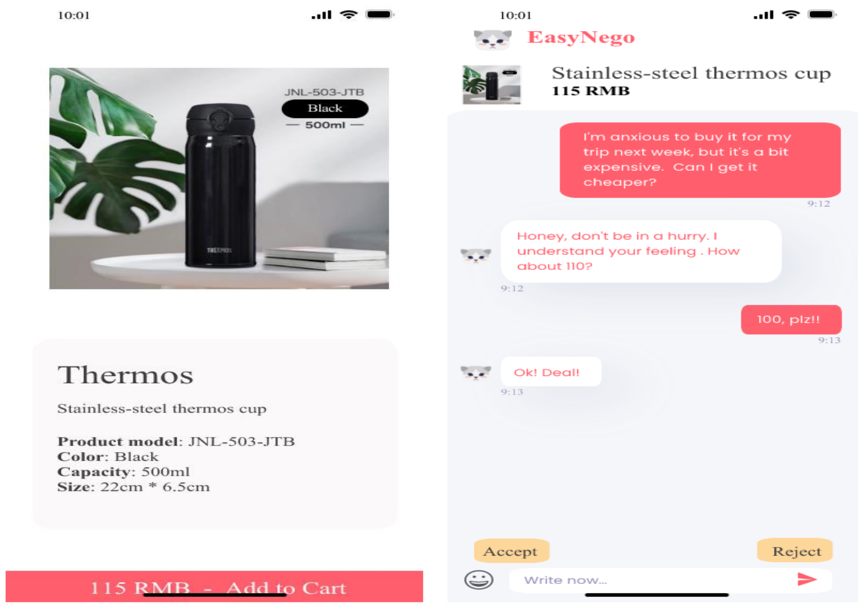

Figure A1. The Negotiation Interface of EasyNego for Pre-test

We recruited 210 people to participate in the pre-test. The participants were randomly assigned into two groups. In the treatment condition (n=107), the agent enabled by the EasyNego system has the emotion processing, analyzing, and responding components. In contrast, the emotional components were blocked in the control condition (n=103). In other words, the agent in the control condition can only provide participants with offers in plain language without any emotional feedback. The experimental procedure was similar to the formal research procedure in section 4.2.

Similar to our main test, we have dropped the sample without making a deal (N=7). The ANOVA results of the pre-test are shown in Figure A2. It indicates that the negotiation rounds to make a deal were significantly fewer in the treatment group (Mean=17.81) than in the control group (Mean=37.36, t=-9.98, p<0.001). The results show that the agent with empathic capability can encourage users to make deals faster than those without. This supports our assumption that integrating emotion processing, analyzing, and responding components in the EasyNego system could provide users with an empathic agent and positively impact the negotiation process.

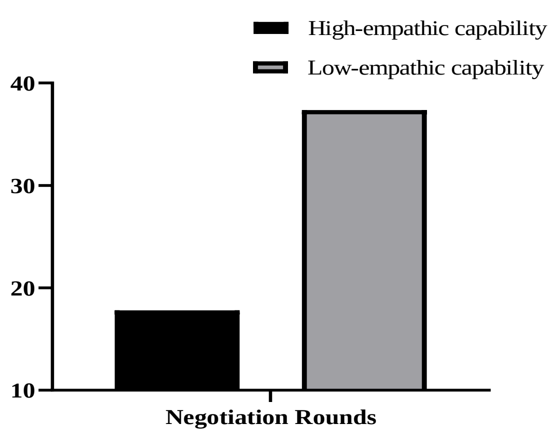

Figure A2. Results of Pre-test

Appendix B Research Procedure Guideline

1. Task Introduction

Please imagine that you are participating in the 618 Shopping Festival[9]. Your task is to consider purchasing a 10000-mAh mobile power pack with Type-C and Lightning charging cables. You will be directed to a simulated shopping website for price negotiation. Please acquire your preferred items at the most favorable price[10]. Please carefully follow the steps outlined below.

2. Shopping Steps

(1) Please navigate to the website link provided and access the interface. From there, select the “Human-agent Negotiation System” option.

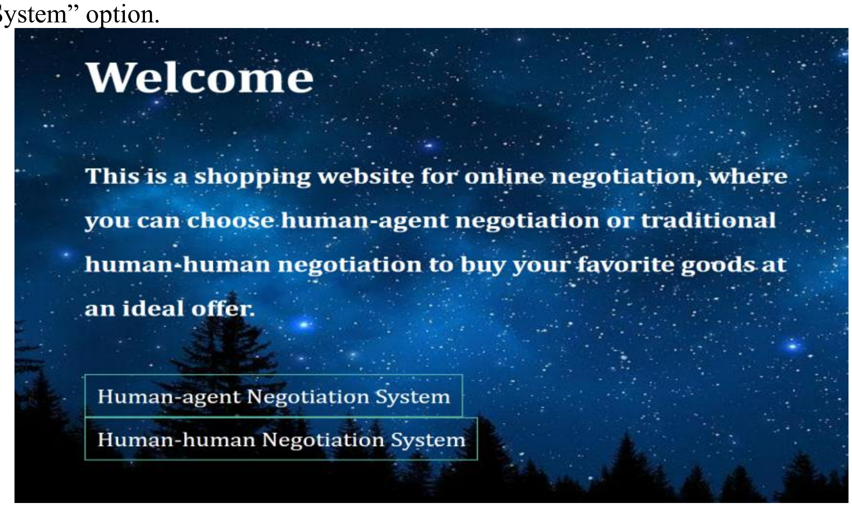

Figure B1. The Welcome Page of the EasyNego System

(2) Please watch the instructional training video and choose the appropriate item to access the negotiation interface. Subsequently, proceed to the top left corner to log in and enter your designated account.

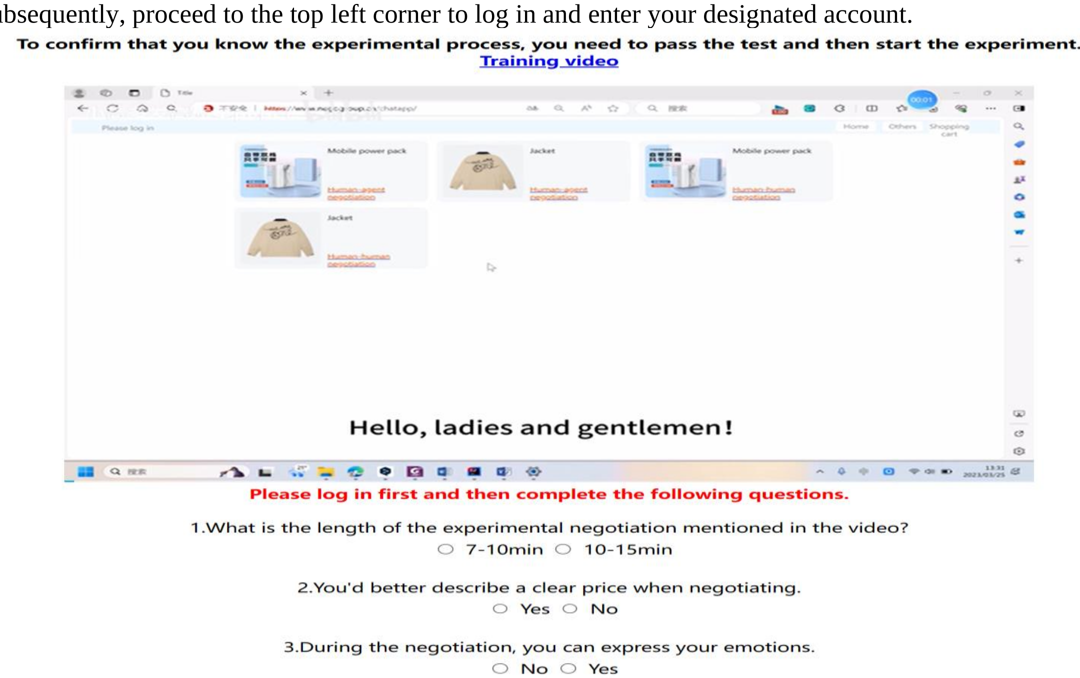

Figure B2. Screenshot of Training Video Page

[9] The “618 Shopping Festival” is a major online shopping event in China, known for its widespread discounts and promotions across various e-commerce platforms.

[10] The website link is https://www.negogroup.cn. If you need a test account, you can contact with the authors.

(3) Please input your username and password.
(4) After logging in, select "Mobile Power Pack" to start the negotiation.

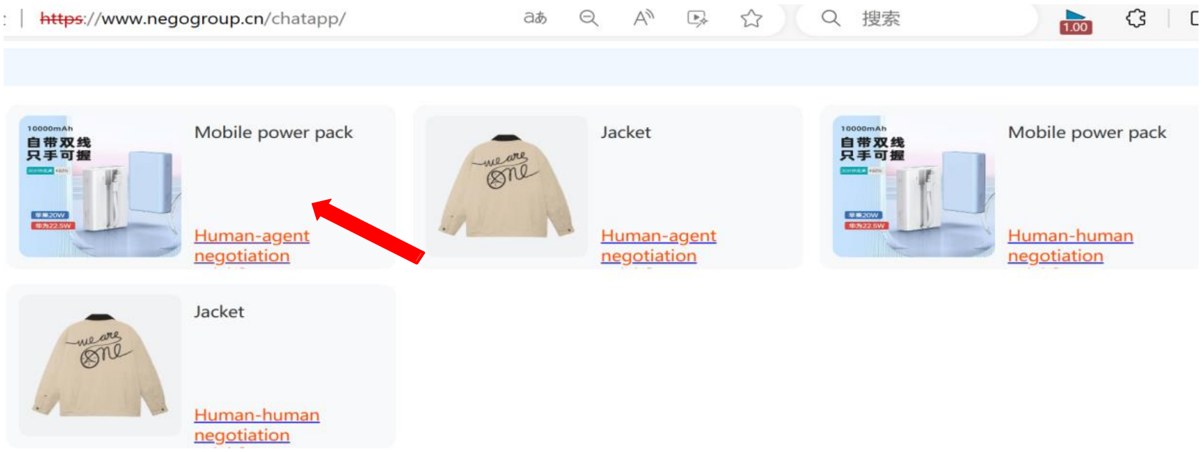

Figure B3. Screenshot of Product Selection

(5) Please pay attention to the following guidelines during your negotiation with the agent:
- You can initiate the negotiation with the EasyNego agent by saying "Hello", "Hi," or any similar salutation. This will prompt the agent to start negotiation.
- To optimize your negotiation consequences, consider starting with a price lower than your expectation. However, please clearly articulate your offer during the negotiation process. For instance, phrases like "Can you sell it to me for 100?" or "How about making a deal at 100?".

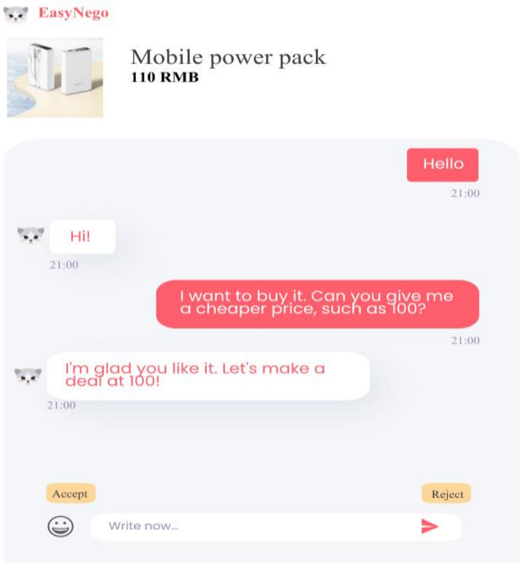

Figure B4. Example of Negotiation Process

(6) If you are satisfied with the price, you can inform the EasyNego agent by saying, "Let's make a deal", and then click the "Accept" button to finish the negotiation. Also, if you prefer not to negotiate further, you can communicate this to the EasyNego agent by saying, "I won't purchase it", and then clicking the "Reject" button to conclude the negotiation.
(7) Upon completion of the negotiation, you will be directed to finish a questionnaire.

Thank you very much for your cooperation.

Appendix C Common Method Bias Tests

According to Lindell and Whitney (2001), we controlled the Marker Variable and estimated the correlation between variables. The results are shown in Table C1. Comparing Table C1 and Table 4, we found the change in correlation coefficients after controlling for the Marker Variable, as shown in Table C2. In addition, we have also conducted common method bias test based on Liang et al. (2007). The results showed no significant change among the important constructs.

Table C1. Correlations after Partialing out Marker Variable Variance

	PEC	TRU	SAT	CUI
Perceived Agent Empathic Capability (PEC)	-			
Trust in the Agent (TRU)	0.67 ***			
Satisfaction towards the Agent (SAT)	0.54 ***	0.63 ***		
Intention to Continuously Use the Agent (CUI)	0.42 ***	0.59 ***	0.75 ***	
Perceived Control over the Negotiation (PCN)	0.32 ***	0.40 ***	0.39 ***	0.36 ***

Notes: ***<0.001, **p<0.01, *p<0.05

Table C2. Change Ratio in Correlations (After vs. Before)

	PEC	TRU	SAT	CUI	PCN
Perceived Agent Empathic Capability (PEC)					
Trust in the Agent (TRU)	0.020				
Satisfaction towards the Agent (SAT)	0.034	0.023			
Intention to Continuously Use the Agent (CUI)	0.055	0.028	0.013		
Perceived Control over the Negotiation (PCN)	0.084	0.059	0.062	0.069	

Table C3. Common Method Bias Test According to Liang et al. (2007)

Construct	Indicator	Substantive Factor Loading (R1)	$R1^2$	Method Factor Loading (R2)	$R2^2$
Perceived Agent Empathic Capability (PEC)	PEC1	0.807 ***	0.651	0.018	0.000
	PEC2	0.807 ***	0.651	0.034	0.001
	PEC3	0.781 ***	0.610	0.016	0.000
Trust in the Agent (TRU)	TRU1	0.849 ***	0.721	0.009	0.000
	TRU2	0.842 ***	0.709	0.080	0.006
	TRU3	0.873 ***	0.762	0.040	0.002
Satisfaction towards the Agent (SAT)	SAT1	0.831 ***	0.691	0.112	0.013
	SAT2	0.899 ***	0.808	0.079	0.006
	SAT3	0.916 ***	0.839	0.058	0.003
Perceived Control over the Negotiation (PCN)	PCN1	0.881 ***	0.776	0.013	0.000
	PCN2	0.888 ***	0.789	0.073	0.005
	PCN3	0.898 ***	0.806	0.147	0.022
	PCN4	0.870 ***	0.757	0.073	0.005
Intention to Continuously Use the Agent (CUI)	CUI1	0.917 ***	0.841	0.068	0.005
	CUI2	0.926 ***	0.857	0.035	0.001
	CUI3	0.931 ***	0.867	0.031	0.001
Average			0.758		0.004

Note: ***p<0.001, **p<0.01