Information & Management 61 (2024) 103931

Contents lists available at ScienceDirect

Information & Management

journal homepage: www.elsevier.com/locate/im

The impacts of live chat on service–product purchase: Evidence from a large online outsourcing platform

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ARTICLE INFO

Keywords:
Live chat
Online outsourcing platform
Informative signals
Affective signals
Purchase decision

ABSTRACT

This study examines the impact of live chat on purchase decisions in the context of online outsourcing platforms. A theoretical research model based on signaling theory is proposed. The results of an econometric model based on a unique dataset from a large online outsourcing platform demonstrate that both affective signals (reflected by politeness and sentiment valence) and informative signals (reflected by information quantity and response timeliness) positively affect purchase decisions. In addition, these effects are found to be significantly influenced by consumers' prior experience. Specifically, the findings show that consumers' prior experience undermines the effect of politeness and sentiment valence on purchase decisions, but strengthens the effect of information quantity. In general, this study not only offers a comprehensive understanding of live chat in an outsourcing platform, but also yields insights into how live chat tools can be designed and used to promote online transactions.

1. Introduction

In today's digitally driven marketplace, online outsourcing platforms (OOPs) have become pivotal hubs connecting consumers with a global pool of service providers. The success of these platforms relies heavily on effective communication channels, with live chat emerging as a crucial tool for facilitating interactions between consumers and service providers. In the midst of this growing digital landscape, live chat has gained recognition as a critical communication tool that can significantly reduce information asymmetry, build trust, and ultimately influence purchasing decisions [57,59]. However, within this dynamic arena, a notable research gap has emerged that warrants our attention: the nuanced impact of live chat's affective and informative dimensions (refer to the Appendix for details on the research gap). While previous researchers have acknowledged that the live chat service of an OOP serves two signaling roles—informative and affective [9,23]—comprehensive studies exploring how these two dimensions of signals affect consumer purchases have been limited. In this context, our study aims to shed light on the underlying effects and potential moderating factors influenced by consumers' prior experiences, thereby contributing to the existing body of knowledge.

The affective dimension in live chat interactions is multifaceted, encompassing the rapport-building aspects of the conversation and emotional tone [18,37]. Politeness is a fundamental component of this dimension, as it directly affects the customer's perception of the service provider's professionalism and courtesy. Politeness fosters a positive atmosphere, reducing the likelihood of misunderstandings and conflicts during the interaction. It can also contribute to the formation of trust, an

The authors are listed with alphabetical order, and they contribute equally. This work was partially supported by National Natural Science Foundation of China from Liqiang Huang (No. 72271217, 71931009, 72332005), from Zhongsheng Hua (No. 71821002), and from Lingfeng Dong (No. 72301087); Zhejiang Provincial Natural Science Foundation of China (No. LR22G010002, LQ23G010002, LY22G010007); National Social Science Foundation of China (No: 22CGL014); Zhejiang Provincial Philosophy and Social Sciences Planning Project (No: 24NDQN007YB); Research Start-Up Fund of Hangzhou Normal University (No. 4135C50221204091), and National Key Research and Development Project (No. 2018YFB1403600).

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https://doi.org/10.1016/j.im.2024.103931
Received 11 June 2021; Received in revised form 28 January 2024; Accepted 5 February 2024
Available online 13 February 2024
0378-7206/

essential element in the decision-making process. Sentiment valence, on the other hand, delves into the emotional content of the interaction [52]. Positive sentiments conveyed during live chat can enhance the overall customer experience by evoking positive emotions and reinforcing the consumer's inclination to make a purchase. Conversely, negative sentiment valence can deter consumers and potentially lead to abandoned transactions. Therefore, the choice of politeness and sentiment valence as indicators of the affective dimension is rooted in their capacity to influence the emotional aspect of the customer experience, which is pivotal in purchase decisions.

In the informative dimension, the quantity of information and response timeliness are selected as significant factors [23,37]. The quantity of information provided during a live chat interaction determines the depth of understanding a consumer gains about the product or service. A comprehensive and well-structured response can equip consumers with the knowledge they need to make informed decisions, potentially increasing the likelihood of a successful purchase. Response timeliness is equally crucial in the informative dimension [55]. In today's fast-paced digital environment, customers often seek quick answers and solutions. Delayed responses can lead to frustration, impatience, and even abandonment of the interaction, negatively impacting the decision-making process. Therefore, information quantity and response timeliness are chosen to represent the informative dimension due to their direct influence on the effectiveness of communication and the consumer's ability to gather information efficiently.

Recognizing that the influence of these affective and informative dimensions may vary among different customers, we introduce a moderator variable, the consumer's prior experience. Consumers on OOPs often come with varying levels of experience, ranging from novices to seasoned professionals [10,46]. Understanding how the impact of politeness, sentiment valence, information quantity, and response timeliness differs based on a consumer's prior experience is essential for tailoring live chat interactions effectively to meet the specific needs of various customer segments. In particular, an experienced consumer can make a rational inference from the live chat message, whereas a novice consumer cannot [14]. For instance, consumers with prior experience on the platform may already possess a certain level of knowledge and familiarity with the services offered [39]. This prior knowledge provides them an advantage in processing information, enabling effective identification and extraction of value from information signals during the communication process. For them, the significance of politeness and sentiment valence in live chat interactions may vary, as they might prioritize efficiency and information depth over emotional aspects [14]. On the other hand, novice consumers often do not have enough knowledge and experience to evaluate the rationality and feasibility of service–product needs confidently [15,60]. This inherent uncertainty can make them particularly reliant on emotional support from service providers during the communication process. Thus, for novice consumers, politeness and sentiment valence could play a more substantial role in shaping their impressions and trust in a platform. The reasons that prior experience should be essentially included could be summarized as the following: (1) consumers with varying levels of prior experience may attribute different levels of importance to politeness, sentiment valence, information quantity, and response timeliness; (2) consumer experience may influence the patterns of decision-making, in that experienced consumers may exhibit more rational decision-making, while novices may be swayed by emotional cues; and (3) as consumers gain experience on a platform, their expectations and preferences may evolve. By considering the consumer's prior experience as a moderator, we can account for these changes and adapt strategies to cater to the evolving needs of different consumer segments.

In light of the complex and evolving nature of OOPs, this research aims to fill a critical knowledge gap by providing a comprehensive understanding of how politeness, sentiment valence, information quantity, and response timeliness in live chat interactions collectively influence purchase decisions. Drawing on the overarching theoretical framework, signaling theory, several related hypotheses have been proposed. By considering the moderating effect of consumers' prior experience, this study not only seeks to contribute to the academic discourse on online marketplaces but also offers practical insights that can be harnessed by platform operators, service providers, and consumers alike to enhance the efficacy of live chat interactions and, consequently, optimize purchase outcomes. In sum, the multifaceted nature of live chat interactions within the online outsourcing context, encompassing the affective and informative dimensions along with the moderator variable of consumers' prior experience, underscores the critical importance of this research. By delving into these dimensions, we aim to provide a nuanced understanding of the factors that shape purchase decisions in the evolving landscape of OOPs.

2. Theoretical background

2.1. Live chat in business

Live chat refers to a web-based function that provides a channel through which consumers can communicate synchronously with service providers in order to reduce information asymmetry, thus enhancing final transactions [59]. Considering the significant role that live chat plays in online shopping, it has attracted wide attention from scholars (see Appendix). For example, Tan et al. [58] suggest that live chat influences consumers' purchase decisions. Similarly, using archival data, Lv et al. [37] and Tan et al. [59] have demonstrated that live chat between both parties has a positive effect on a consumer's purchase decisions. Moreover, Hong et al. [18] indicate that direct messaging with a potential employer increases a worker's probability of being hired by 8.9%. In addition, Sun et al. [57] investigate how the fit between live chat and platform information affects traffic-to-sales conversion. Other related works also reveal the relationships between live chat usage and consumers' behavior, such as their attitudes, beliefs, and level of satisfaction (e.g., [23,38]).

It is worth noting that, to date, the prevailing body of literature has primarily focused on providing direct evidence of the impact of live chat on various business outcomes, such as purchase decision [59], tendency to disintermediation [13], and traffic-to-sales conversion [57]. However, the underlying mechanism of live chat is largely unexplored, with one exception: Hong et al. [18] build on the research gap that "no empirical examination has been conducted to quantify how live chat affects the decision to purchase" and find that direct messaging for workers depends significantly on their politeness, which is further called a "politeness effect." Building on the current literature, our study extends Hong et al. [18]'s work by a deeper exploration of how various communication characteristics, other than politeness itself, bring out decision making. In line with suggestions from previous studies that consider main features such as politeness and information quantity, our work takes these characteristics into consideration, because it is suggested that varying characteristics typically transfer different types of signals in communications [9,57]. To further understand the role of live chat, we draw on signaling theory.

2.2. Signaling theory

Signaling theory, proposed by Spence [56], pertains to the reduction of information asymmetry between two parties in economic and social environments where one party in a relationship has more or better information than the other party in the precontractual situation. The theory posits that one party sends signals to the other by conveying valuable information to reduce uncertainty and obtain desired outcomes. It also suggests that the transfer of a signal is determined not only by actors such as signalers who send messages and receivers who receive messages, but also by what type of information is transferred [10]. Considering its great power, it has been widely applied in previous studies in areas such as electronic commerce [46] and virtual communities [9], to understand how two parties address information asymmetry in the precontractual situation. In service-related production transactions, synchronous live chat is considered one of the most effective means of transferring signals from service providers to consumers [18].

According to studies in relation to signaling theory, there are two types of signals in consumer research, the affective signal and the informative signal [9,41]. The affective signal refers to a linguistic feature that provides emotional expression, while the informative signal refers to what type of information a message transfers in order to reduce uncertainty and equivocality between communication parties [62]. With respect to affective signals, valence and emotions are the most key concerns regardless of the research contexts varying from the online brand community to the online rating discussion [52]. In terms of the valence dimension, discussions of affective signals are generally related to sentiment valence [44,50]. Sentiment valence refers to the overall orientation tone in linguistic behavior (e.g., positive, neutral, or negative) expressed by the service provider [6,29]. It is generally embedded in a piece of online message, which is used to promote the effectiveness of communication [66]. Relating to the focal context of online communication, politeness could be most representative of the emotional dimension because it is closely related to how we express and regulate others' emotions in social interactions [20,30]. As Morand and Ocker [42] said," politeness is a form of emotion-work in computer-mediated communication." Politeness refers to the act of showing consideration, respect, and kindness toward others in social interactions [7]. In commercial contexts, politeness often satisfies consumers' needs for positive feelings and satisfaction. Prior research has confirmed that a polite communication can influence one's emotional responses and trust [30,48]. Although sentiment valence and politeness are closely associated with linguistic features in text semantic mining, they are two different concepts in language analysis [22]. The former reflects a linguistic tone, while the latter reflects a linguistic style. A person may exhibit negative sentiment toward something while still displaying politeness in their language, or may convey positive sentiment while being impolite. In our study, politeness and sentiment valence are included as manifestations of affective signal.

Informative signaling is used to enhance information diagnostics, thus reducing uncertainty and equivocality of signal receivers in information processing [9,62]. With this aspect, it is argued that information quantity and response timeliness are important elements designed to reduce uncertainty and equivocality. Information quantity refers to the total amount of information a signaler sends to a receiver. A majority of studies confirm information quantity as a crucial factor in removing uncertainty [63]. Response timeliness is defined as how quickly consumers receive a response after sending an instant message [55]. A rapid response enables the signaler to help the receiver structure the particular problem they face quickly, to reduce the occurrence of ambiguity and foster consensus.

Although signaling theory assumes the importance of signals, receivers are boundedly rational and cannot focus equally on all available signals [47,64]. This limitation has been highlighted by Bergh et al. [5], where the authors demonstrated the insufficiency of signaling theory in explaining how receivers interpret and respond to signals. As signaling aims to reduce information asymmetry, consumers' utilization of signals is likely influenced by their information needs during the pre-purchase stage. This is highlighted by prior research on consumers' information-seeking behavior, which indicates that consumers' information requirements are primarily shaped by their prior experience [10,46]. Given these considerations, consumers may exhibit varying preferences when confronted with a variety of signals, depending on their experiences. Accordingly, fitting into this study, we seek to understand whether and how various signals of live chat in the context of OOPs influence consumers' purchase decision and how consumers' prior experience moderates the impact of various communication characteristics on purchase decision. The following will theorize about the underlying mechanism based on signaling theory and prior literature.

3. Hypothesis development

The research model is shown in Fig. 1, which summarizes the relationships we seek to test, namely, the main effects of various types of signals on purchase decisions and the moderating effects of prior experience.

3.1. Affective signaling

Politeness plays a crucial role in the context of OOPs, where the successful production of customized service offerings is heavily reliant on cooperation between consumers and service providers [17]. In this regard, politeness often satisfies consumers' subjective and emotional needs for positive feelings and satisfaction. When service providers use polite language in their messages, they signal their trustworthiness, which helps to establish and maintain strong relationships with consumers, leading to desirable outcomes [30]. In contrast, service providers who fail to treat their consumers with politeness risk losing them gradually. Per signaling theory and prior work, consumers need to rely on politeness as a signal of whether service providers are easy to cooperate with and make decisions accordingly [10,18]. Accordingly, we posit that politeness can be treated as an important determinant that significantly influences a consumer's purchase decision. We hypothesize that

H1. Politeness is positively associated with purchase decisions.

In OOPs, consumers try to describe what they want regarding a focal service–product such as APP design [17,32]. It is not rare that a service provider expresses their tone when facing a coming task, either having high confidence of successful completion or low confidence, based on evaluations. In their communications, this type of tone can be perceived and interpreted by potential consumers, which further influences consumers' decisions. For a positive tone, service providers show capacities and enthusiasm by sending positive emotional signals, which can help improve consumers' trust perception and create a sense of confidence [66]. Therefore, we hypothesize that

H2. Sentiment valence is positively associated with purchase decisions.

3.2. Informative signaling

Reducing uncertainty is important to consumers due to the complex nature of outsourcing services (idiosyncratic and highly customized; [32]). Consumers have to obtain sufficient information through effective communication and coordination to successfully reach an agreement [17]. In OOPs, live chat allows consumers to inquire, obtain, or exchange information from the provider about the services. From the perspective of signaling theory, the information quantity sent from service providers can convey an informative cue or signal where consumers obtain information that effectively reduces uncertainty and information asymmetry [9]. It is commonly believed that larger amounts of information can reduce perceived risk and uncertainty, thereby fostering a positive attitude toward purchase behavior [59,63]. Based on the above discussions, we hypothesize that

H3. Information quantity is positively associated with purchase decisions.

In an online outsourcing marketplace, effective communication and coordination are prerequisites to reach an outsourcing project transaction [17]. For instance, a timely and rapid response from a service

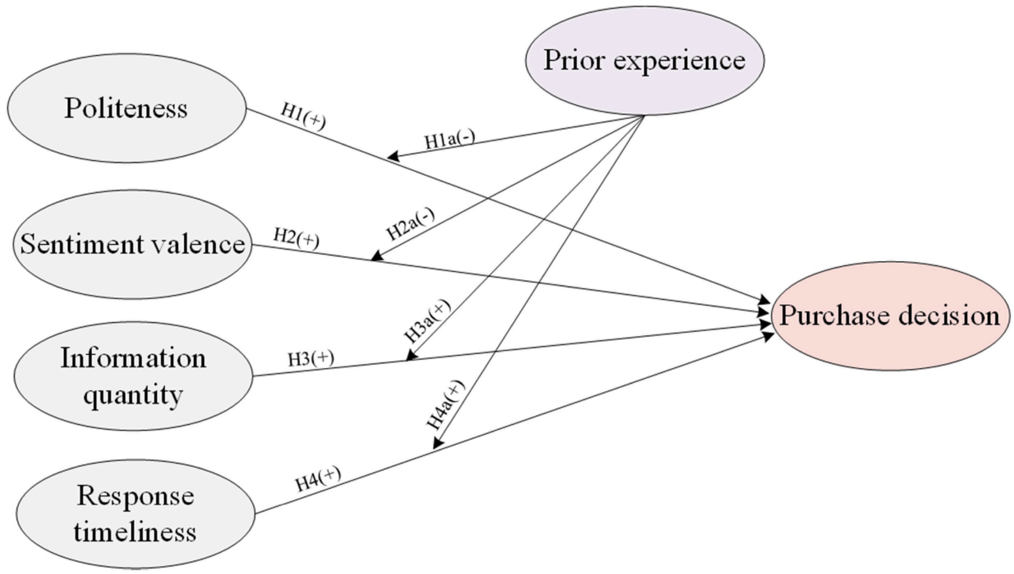

Fig. 1. Research model.

provider through live chat helps consumers articulate the particular problems they are facing and clarify the goals of the outsourced service sought. In this sense, the rapid response of service providers transmits an information signal to eliminate consumers' perception of ambiguity. Also, it is highlighted by telepresence theory that a quick response to the consumer's request could increase perceived interactivity between consumers and service providers, which helps consumers eliminate ambiguity through regular back-and-forth dialog [55]. Conversely, slow communication may frustrate consumers and reduce their behavioral intentions. Therefore, response timeliness is expected to positively influence purchase decision. Thus, we hypothesize that

H4. Response timeliness is positively associated with purchase decisions.

3.3. Moderation effect of prior experience

While prior discussion suggests a positive relationship between politeness and purchase decision, the relationship may be contingent on consumers' prior experience. Specifically, novice consumers tend to make more emotional, rather than rational, inferences about the signals they receive [14]. With this in mind, when consumers communicate with service providers, they may prefer to rely on politeness to judge whether the service provider is easy to cooperate with or creates a sense of confidence [18]. However, as consumers' transaction experience increases, they often transition from more emotionally driven decision-making to a more rational and analytical approach, such as establishing clear service specifications and standards to regulate cooperation between two parties, thereby weakening the impact of politeness. Therefore, we predict that prior experience will undermine the impact of politeness in purchase decisions:

H1a. Prior experience negatively moderates the relationship between politeness and purchase decision.

With respect to sentiment valence, we posit that its impact on purchase decisions is contingent on prior experience. Specifically, compared with experienced consumers, novice consumers often do not have enough knowledge and experience to evaluate the rationality and feasibility of service–product needs confidently [60]. This inherent uncertainty can make them particularly reliant on encouragement and reassurance from service providers [15]. In such situations, the significance of positive sentiment expressed by service providers is notably amplified. Novice consumers often derive comfort from an enthusiastic and affirmative tone conveyed by service providers, as it serves to alleviate their insecurities and uncertainties pertaining to their choices. Conversely, experienced consumers have a certain level of professional knowledge and familiarity with related service transactions, enabling them to make rational inferences about the rationality and feasibility of their own service needs [14,16], thereby mitigating the influence of sentiment valence on their decision-making processes. Taken together, we predict that prior experience will weaken the influence of sentiment valence:

H2a. Prior experience negatively moderates the relationship between sentiment valence and purchase decision.

While prior discussions suggest a positive link between information quantity and purchase decisions, this connection may be influenced by prior experience. Experienced consumers, compared with novices, possess extensive knowledge and familiarity with service transactions [39,51]. This prior knowledge provides them with an advantage in processing information, enabling effective identification and extraction of valuable information during interactions [15]. Moreover, experienced consumers tend to approach decision-making with greater confidence due to their familiarity with service transactions. This confidence allows them to handle substantial volumes of information during communication with service providers without feeling overwhelmed. Conversely, novice consumers, lacking the benefit of prior transaction experience, may encounter challenges in processing information. They may struggle to discern critical details from volumes of information, potentially leading to decision-making difficulties. Therefore, we predict that prior experience will strengthen the impact of information quantity in purchasing decision. We hypothesize that

H3a. Prior experience positively moderates the relationship between information quantity and purchase decisions.

While a positive relationship between response timeliness and purchase decisions has been suggested in prior discussions, this relationship may depend on prior experience. Specifically, compared with naive consumers, members with more experience who engage in social interactions are more goal-directed [43]. As Sánchez-Franco and Roldán [53] said, "goal-directed flow activities are instrumental and utilitarian in nature," characterized by valuing time and efficiency, and result in time sensitivity. As a result, they place more importance on promptly resolving specific inquiries and gaining a precise understanding of outsourced service objectives. In contrast, novice consumers are often unfamiliar with typical expectations and standards regarding response times in service transactions. They may not have a frame of reference to gauge what constitutes a fast or slow response, and thus the impact of response timeliness may be less pronounced. Hence, it is hypothesized that

H4a. Prior experience positively moderates the relationship between response timeliness and purchase decisions.

4. Research methodology

4.1. Research context and data collection

We used a large-scale granular dataset from a large online outsourcing platform, one of the largest OOPs in China. It was established in 2006 and had attracted over 32.4 million registered members by the end of 2022. We chose this platform as the context to examine our hypotheses because (1) it is one of the largest OOPs in Asia; (2) the platform has a typical live chat component for consumers and service providers to communicate instantly, as well as a record of detailed chat conversations, such as the message content, timestamps for each message, and information about users who use live chat; and (3) the platform has a large number of transactions that enable the selection of diversified outsourcing services (e.g., software development, programming, and logo design). The dataset we obtained pertains to 1607 consumers from June 1, 2018 to December 31, 2018 who connected 216,762 chat records and 4587 service providers. In our dataset, each chat record between the consumer and the service provider is tied to a particular transaction, and each transaction incorporates associated information about the service provider, including time-invariant (e.g., registration time) and time-variant characteristics (e.g., history information of transactions and reviews). Because service products are highly customized, communication between consumers and service providers is not limited to the communication before purchase decision, but also includes services after purchase. Thus, we divided the communication records between the consumer and the service provider into pre- and post-purchase communications, based on the timing of purchase decisions. Our analyses focus squarely on pre-purchase communication because post-purchase communication, by definition, cannot influence consumers' purchase decisions and thus is beyond the scope of this research.

4.2. Operationalization

Purchase decision. The dependent variable in this study is whether a consumer makes a purchase decision after the conversation, that is, a binary variable. In line with prior research such as Tan et al. [59], we coded our dependent variable *Purchase* as 1 if the consumer made a purchase decision, and as 0 otherwise.

Politeness. The politeness of a message measures the degree to which the service provider is polite in the conversation. To assess the effect of politeness on purchase decision, we employed text mining and a human labeling method [18]. The specific steps are as follows. Since the messages are in Chinese, we first employed a Python package, *Jieba*, a popular technique for Chinese segmentation, to divide the service provider's messages into words [33,49]. Then, following Lee et al. [30] and Humphreys and Wang [20], we constructed linguistic markers related to politeness according to the Chinese dictionary and counted the occurrences of the politeness markers in a conversation. Finally, we measured the politeness level of the service provider by dividing the count of politeness markers by the number of words or phrases [61]:

$$Politeness = \frac{\sum_{i=1}^{i} politeness_i}{n} \tag{1}$$

Sentiment valence. We calculated the sentiment valence of service providers' messages based on the SVM (support vector machine) algorithm in *sklearn* (a Python package; [69]). The specific steps are as follows: First, a service provider's messages were split into words by the Python package *Jieba* [34]. Second, in order to understand the importance of each word in conversion, it is essential to measure their weight, making the classification more accurate. We then calculated the weight of each word based on TF-IDF (term frequency—inverse document frequency), which has been used widely in previous work [36,54]. TF indicates how many times a word appears in a conversation, and IDF measures the percentage of all messages in a collection [28]. Third, since SVM requires the input to be a vector, we used the VSM (vector space model) method to transfer the messages into a vector. Then the sentence was classified into one of three categories according to its sentiment valence, negative, neutral, and positive. The sentiment scores of the above three categories were −1, 0, and 1, respectively [2]. In line with Zhang et al. [66], the *sentiment valence* of the service provider was calculated by the average sentiment valence of all service provider's messages. The formula is shown below:

$$c_i = TF * IDF \tag{2}$$

$$sentiment = \frac{\sum_{i=1}^{i} sentiment_i}{n} \tag{3}$$

Information quantity. A larger amount of information can increase a consumer's understanding of the outsourced services, which should be helpful in eliminating uncertainty and increasing customers' probability of purchasing [63]. Following Lv et al. [37], the *information quantity* was operationalized by the total number of replies that a service provider offered the consumer. In the robustness check section, we respectively employed the total length of replies of the service provider and the total length of the negotiation (i.e., the total length of messages of the service provider, adding the total length of the consumer's message) as two other ways to measure information quantity.

Response timeliness. Response timeliness refers to how quickly consumers receive a reply from the service providers [66]. The more time elapses until the service provider responds to the consumer, the lower the response timeliness. Therefore, the relationship between response timeliness and response time is inversely proportional. Bear this in mind, we operationalized it in terms of inverse average response time until a consumer receives a reply from the service provider about their inquiries in conversation:

$$response\_timeliness = 1 \Bigg/ \frac{\sum_{i=1}^{n} reponse\_time_i}{n} \tag{4}$$

In the process of communication, multiple rounds of dialog may take place. When the last round of conversation is over, it may be a long time before the next round that discusses another topic, so the time difference between the last round's closing sentence and the first sentence of the next round is not suitable for calculation. To eliminate this impact, the calculation of response time is carried out within the same round of conversation. As shown in Fig. 2, there are four situations for calculating the response time in the same round of conversation:

(1) If the consumer and service provider send messages one by one, we calculate the response time in terms of the time interval between these messages; that is,

$$response\_time = reponse\_time_i \tag{5}$$

(2) If the service provider replies to consecutive messages from the consumer, the response time is calculated as follows:

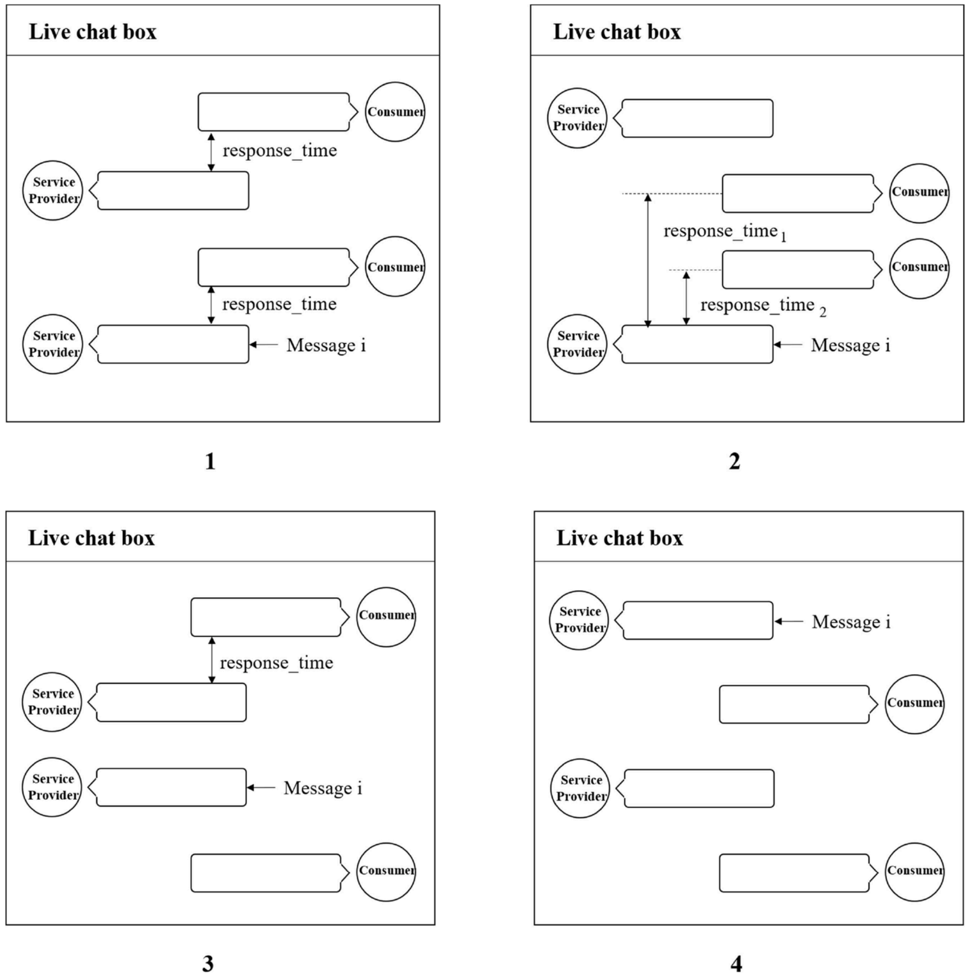

Fig. 2. The four operationalizations of response time.

$$response\_time = \frac{\sum_{k=1}^{k} response\_time_k}{k} \tag{6}$$

where k represents the unit that the consecutive messages were asked by consumers.

(1) If the service provider consecutively replies to one message from the consumer, the response time is calculated in terms of the time interval elapsed until the consumers receive the first reply from the service provider about their inquiries in conversation.
(2) If the message sent by the service provider is the first message in the conversation, then the message is not counted.

Prior experience refers to the degree to which a consumer is knowledgeable about the outsourcing transaction [67]. According to Kim and Krishnan [25], the cumulative number of online transactions indicates the level of prior experience. In this platform, the higher the prior purchase volume of a consumer, the higher the degree of prior experience. In this study, we employed the cumulative number of purchase volumes prior to the focal conversation to measure the consumer's prior experience.

We controlled for a set of other factors that potentially explain the purchase decision in an outsourcing platform. These control variables include (1) a "0–1″ binary variable to represent whether a service provider has an authentication prior to the focal conversation (*Authentication*) [65]; (2) the number of years between the current date and the date of the service provider's registration on the platform prior to the focal conversation (*Syear*) [11]; (3) the number of previous transactions sold prior to the focal conversation (*Volume*) [59]; (4) the average rating of the focal product prior to the focal conversation (*Reputation*) [8]; (5) the spatial distance in kilometers between the service provider and the consumer based on the longitudes and latitudes of their locations (*Distance*) [19]; (6) the registration time (in years) of consumers in the platforms prior to the focal conversation (C*year*) [11]; (7) the number of other service providers that consumers communicate with (competition) [24,40]; (8) whether the consumer initiated a message to the service provider (initiator) [18].

4.3. Model specification and estimation

Tables 1 and 2 show the descriptive statistics and matrix of correlations, respectively. The correlation coefficients among the independent variables are less than 0.7; the variance inflation factor (VIF) values for all of these variables range from 1.03 to 1.60, with an average value of 1.19. Thus, multicollinearity among the key variables was not a serious concern [68].

Similarly to prior research such as Pu et al. [49], we used a logit regression model to analyze the data by considering the dependent variable as binary. Meanwhile, due to the existence of interaction terms, we employed the hierarchical regression model to investigate the main effect and the moderating effect [11]. To reduce the possible multicollinearity, all independent variables were mean-centered before the interaction terms were established. The regression model is as follows:

$$logit\left[P\left(purchase_j = 1 \middle| X_i\right)\right] = \beta_0 + \beta_1 \cdot Politeness_i + \beta_2 \cdot Sentiment_i + \beta_3 \cdot Quantity_i + \beta_4 \cdot Timeliness_i + \beta_5 \cdot Experience_i \cdot Politeness_i + \beta_6 \cdot Experience_i \cdot Sentiment_i + \beta_7 \cdot Experience_i \cdot Quantity_i + \beta_8 \cdot Experience_i \cdot Timeliness_i + \sum \gamma \cdot Controls_i + \varepsilon_i \tag{7}$$

where *i* represents the focal conversation, $P(purchase_j = 1|X_i) \in \{1,0\}$, 1 represents the consumer making a purchase decision and 0 is otherwise; *Controls* includes *Authentication*, *Syear, Volume, Reputation, Distance, Experience, Cyear, Competition*, and *Initiator*.

5. Results

5.1. Estimation results

The results are shown in Table 3 and Fig. 3. Model 1 included the control variable and Model 2 tested the main effect. Models 3–6 tested the moderating effects by sequentially adding interaction items. In addition, the significance of regression coefficients did not change, indicating that these models have good stability.

The results show positive associations of politeness ($\beta = 8.472, p < 0.01$), sentiment valence ($\beta = 1.416, p < 0.01$), information quantity ($\beta = 0.683, p < 0.01$) and response timeliness ($\beta = 0.280, p < 0.01$) with purchase decision. Thus, Hypotheses 1–4 are supported. With respect to the moderation effects, interesting results were uncovered. As shown in Table 3, we found that prior experience has a negatively significant moderating effect on politeness ($\beta = -3.034, p < 0.01$) and sentiment valence ($\beta = -0.490, p < 0.01$), but strengthens the impact of information quantity ($\beta = 0.0913, p < 0.01$) on purchase decision. Therefore, Hypotheses 1a, 2a, and 3a are supported, but no significant moderation effect is identified from response timeliness and purchase decision ($\beta = -0.0276, p = 0.138$).

5.2. Robustness checks

In Table 4, we used the results of Model 6 in Table 3 as the baseline results. Several robustness checks were performed. First, alternative measurement is an effective way to conduct a robustness check [17]. (1) Sentiment valence was operationalized using an alternative computation method. Specifically, we used the Baidu Sentiment Analysis API interface (BD_API) to calculate sentiment valence [3]. BD_API is the leading Chinese natural language processing platform of short text. As shown in Model 7 of Table 4, the findings demonstrate that our results are robust. (2) The length of the message shares the same characteristic with information quantity. As shown in Model 8 of Table 4, the findings demonstrate that our results are robust. (3) To explore more regarding the negotiation, we performed additional analysis by using the total length of the negotiation (i.e., the total length of messages of the service provider, adding the total length of the consumer's message) to measure information quantity. As shown in Model 9 of Table 4, the results show consistent findings. Second, analyzing data with alternative models is also another way to check the robustness [11]. In line with Tan et al. [59], we employed the ordinary least squares method (see Model 10 in Table 4). No divergent findings were found, which further demonstrates

Table 1
Descriptive statistics of variables.

Construct	Measure Item	Mean	Std.Dev.	Min	Max
Purchase decision	*Purchase*	0.111	0.314	0	1
Politeness	*Politeness*	0.052	0.064	0	1
Sentiment valence	*Sentiment*	0.132	0.279	−0.833	1
Information quantity	*Quantity*	14.389	17.782	1	292
Response timeliness	*Timeliness*	0.057	0.244	0.000104	4
Authentication	*Authentication*	0.120	0.325	0	1
Service provider registration time	*Syear*	2.681	0.865	0.071	4.172
Past sales volume	*Volume*	2680.709	4886.470	0	19,124
Reputation	*Reputation*	4.826	0.797	0	5
Spatial distance	*Distance*	1076.331	1201.580	1	7393.780
Prior experience	*Experience*	5.113	18.482	0	592
Consumer registration time	*Cyear*	1.877	2.023	0.00273	12.060
Competition	*Competition*	1.896	4.138	0	31
Initiator	*Initiator*	0.894	0.307	0	1

Table 2
Correlation matrix.

Variable	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	VIF
V1 Purchase	1.00														
V2 Politeness	0.11	1.00													1.10
V3 Sentiment	0.09	0.18	1.00												1.06
V4 Quantity	0.19	−0.00	−0.08	1.00											1.09
V5 Timeliness	0.14	0.09	0.06	0.16	1.00										1.07
V6 Authentication	0.05	−0.06	0.03	−0.08	−0.09	1.00									1.09
V7 Syear	0.14	0.02	0.07	−0.04	−0.03	0.16	1.00								1.48
vol	0.04	0.10	0.03	0.14	0.16	−0.18	0.54	1.00							1.60
V9 Reputation	0.04	0.06	0.01	0.12	0.09	−0.10	−0.21	0.29	1.00						1.11
V10 Distance	−0.04	0.09	0.05	−0.05	−0.02	0.06	0.02	0.01	−0.03	1.00					1.03
V11 Experience	−0.02	0.01	0.10	−0.04	−0.01	−0.09	−0.03	0.16	0.09	−0.02	1.00				1.36
V12 Cyear	−0.04	0.01	0.01	−0.03	−0.02	0.07	0.01	−0.04	0.01	0.03	0.42	1.00			1.23
V13 Competition	−0.07	0.07	0.06	−0.12	−0.00	0.13	0.11	−0.06	−0.04	0.12	0.25	0.02	1.00		1.14
V14 Initiator	0.03	−0.16	−0.03	−0.12	0.05	−0.04	0.03	0.05	−0.02	−0.05	−0.01	−0.03	0.12	1.00	1.09
Mean VIF															1.19

Table 3
Regression results.

Variables	M1	M2	M3	M4	M5	M6
Politeness		5.518***	6.726***	6.214***	8.282***	8.472***
		(0.561)	(0.741)	(0.750)	(0.884)	(0.898)
Sentiment		0.936***	0.945***	1.439***	1.411***	1.416***
		(0.169)	(0.169)	(0.218)	(0.227)	(0.228)
Quantity		0.776***	0.777***	0.787***	0.639***	0.683***
		(0.0518)	(0.0519)	(0.0516)	(0.0558)	(0.0638)
Timeliness		0.244***	0.244***	0.244***	0.249***	0.280***
		(0.0250)	(0.0250)	(0.0250)	(0.0252)	(0.0322)
Experience*Politeness			−1.119***	−0.108***	−2.895***	−3.034***
			(0.417)	(0.411)	(0.604)	(0.600)
Experience*Sentiment				−0.497***	−0.494***	−0.490***
				(0.135)	(0.130)	(0.126)
Experience* Quantity					0.128***	0.0913***
					(0.0179)	(0.0313)
Experience* Timeliness						−0.0276
						(0.0186)
Authentication	0.580***	0.832***	0.849***	0.856***	0.789***	0.777***
	(0.117)	(0.124)	(0.124)	(0.124)	(0.125)	(0.126)
Syear	1.460***	1.239***	1.242***	1.246***	1.231***	1.227***
	(0.103)	(0.105)	(0.106)	(0.106)	(0.105)	(0.105)
Volume	0.251***	0.146***	0.150***	0.151***	0.141***	0.140***
	(0.0286)	(0.0297)	(0.0300)	(0.0299)	(0.0295)	(0.0294)
Reputation	1.755**	1.500**	1.501**	1.504**	1.491**	1.482**
	(0.727)	(0.662)	(0.678)	(0.689)	(0.668)	(0.665)
Distance	−0.0391***	−0.0441***	−0.0429***	−0.0428***	−0.0487***	−0.0492***
	(0.0132)	(0.0137)	(0.0138)	(0.0138)	(0.0139)	(0.0140)
Cyear	−0.0708***	−0.0725***	−0.0580**	−0.0551**	−0.0954***	−0.0981***
	(0.0215)	(0.0222)	(0.0226)	(0.0226)	(0.0251)	(0.0252)
Competition	−0.458***	−0.480***	−0.466***	−0.464***	−0.502***	−0.505***
	(0.0522)	(0.0568)	(0.0572)	(0.0571)	(0.0582)	(0.0581)
Initiator	0.341**	0.737***	0.745***	0.734***	0.751***	0.755***
	(0.139)	(0.147)	(0.149)	(0.149)	(0.151)	(0.150)
Constant	−5.391***	−7.025***	−7.104***	−7.638***	−7.354***	−7.345***
	(1.296)	(1.200)	(1.228)	(1.266)	(1.231)	(1.225)
Observations	7876	7876	7876	7876	7876	7876
Pseudo R^2	0.073	0.164	0.165	0.167	0.173	0.174
Wald c^2	300.00***	606.58***	610.21***	631.54***	664.25***	666.69***
Log pseudolikelihood	−2536.063	−2287.158	−2284.640	−2280.449	−2260.375	−2259.453
AIC	5090.126	4600.316	4597.281	4590.898	4552.749	4552.907
BIC	5152.764	4690.793	4694.718	4695.295	4664.106	4671.224

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

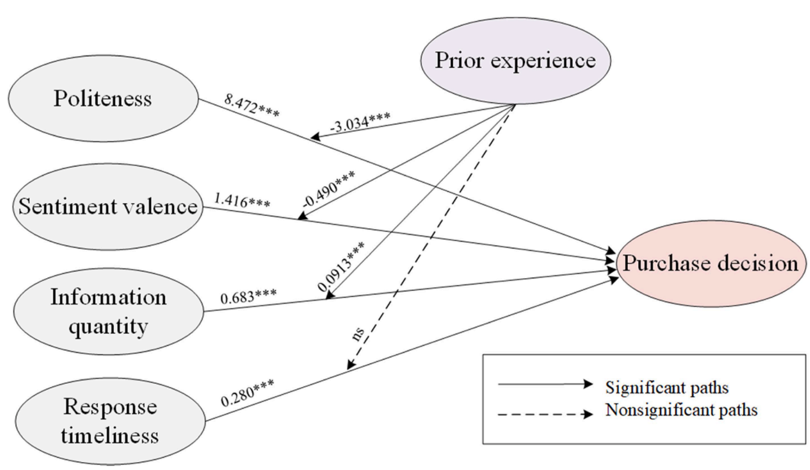

Fig. 3. The revised research model.

the robustness of the findings.

6. Discussion

Based on signaling theory, this article explores whether signals of live chat influence consumers' purchase decisions, and how prior experience moderates the effects. As predicted, we found that politeness, sentiment valence, information quantity, and response timeliness have positive effects on purchase decision. Prior experience weakens the influence of politeness and sentiment valence on purchase decision, but strengthens the effect of information quantity. Interestingly, prior experience does not significantly moderate the relationship between response timeliness and purchase decision. This may be due to the dual influence of prior experience. On one hand, an experienced consumer

Table 4
Robustness checks.

Variables	M7	M8	M9	M10
Politeness	8.049***	8.339***	9.377***	0.856***
	(0.915)	(0.914)	(0.970)	(0.0902)
Sentiment	2.226***	1.307***	1.509***	0.121***
	(0.213)	(0.223)	(0.228)	(0.0181)
Quantity	0.704***	0.481***	0.620***	0.0483***
	(0.0649)	(0.0558)	(0.0475)	(0.00556)
Timeliness	0.268***	0.295***	0.248***	0.0183***
	(0.0336)	(0.0287)	(0.0338)	(0.00223)
Experience*Politeness	−3.001***	−3.186***	−3.526***	−0.328***
	(0.620)	(0.632)	(0.662)	(0.0451)
Experience*Sentiment	−0.488***	−0.469***	−0.520***	−0.0389***
	(0.126)	(0.126)	(0.125)	(0.00982)
Experience*Quantity	0.0889***	0.142***	0.0708***	0.0124***
	(0.0333)	(0.0505)	(0.0197)	(0.00289)
Experience* Timeliness	−0.0312	−0.0142	−0.0112	−0.00101
	(0.0197)	(0.0114)	(0.0212)	(0.00107)
Authentication	0.759***	0.801***	0.811***	0.0773***
	(0.127)	(0.127)	(0.127)	(0.0129)
Syear	1.126***	1.172***	1.232***	0.127***
	(0.105)	(0.104)	(0.104)	(0.0115)
Volume	0.120***	0.119***	0.127***	0.0121***
	(0.0291)	(0.0295)	(0.0295)	(0.00234)
Reputation	1.452**	1.390**	1.465**	0.0337***
	(0.624)	(0.645)	(0.651)	(0.0119)
Distance	−0.0501***	−0.0458***	−0.0449***	−0.00453***
	(0.0141)	(0.0140)	(0.0141)	(0.00136)
Cyear	−0.0936***	−0.0877***	−0.0960***	−0.00768***
	(0.0251)	(0.0245)	(0.0251)	(0.00184)
Competition	−0.492***	−0.534***	−0.558***	−0.0366***
	(0.0586)	(0.0573)	(0.0573)	(0.00376)
Initiator	0.731***	0.804***	0.724***	0.0710***
	(0.151)	(0.150)	(0.151)	(0.0109)
Constant	−8.382***	−7.341***	−8.907***	−0.129***
	(1.157)	(1.211)	(1.217)	(0.0338)
Observations	7876	7876	7876	7876
R^2	–	–	–	0.115
Pseudo R^2	0.193	0.178	0.187	–
Wald c^2	742.94***	625.31***	682.52***	–
F	–	–	–	44.48***
Log pseudolikelihood	−2208.617	−2249.090	−2226.037	–
AIC	4451.235	4532.179	4486.073	3233.537
BIC	4569.552	4650.496	4604.39	3351.854

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

has a stronger goal in mind [43]. Accordingly, a timely and rapid response from a service provider is more likely to help consumers clarify their goals immediately. On the other hand, when consumers rank relatively high in experience, they may pay more attention to the information value [15]. However, a slower response would be judged to be more valuable because a later response means that the service providers can thoughtfully interpret the information query and more clearly articulate their response [63].

6.1. Limitations and future research

Before exploring the implications that this work holds in both theory and practice, the following will outline the limitations of this research with the aim of encouraging future research on this topic. This study mainly centers around granular data collected from this platform, which may, to some extent, hinder the generalizability of the findings. Among e-commerce platforms, only a few have developed live chat tools (such as Ali Wangwang in Taobao); and some well-known platforms such as Amazon do not use live chat [37,59]. Thus, it is still unclear whether our research conclusions can be applied to such e-commerce platforms, which mainly focus on commodity products. Studying live chat in a much broader context may provide a deeper understanding of how to optimize the use of technology-based interpersonal interaction.

Second, although our findings are robust, we cannot reject the possible influences of potential context-oriented factors. For instance, previous studies suggest that message completeness and relevance may affect communication performance. In this study, we keep the research boundary at one level by capturing the big picture of communication messages (i.e., information quantity and timeliness), while neglecting to go to a deeper level by mining the meanings of the message itself, mainly because the analysis of message content by mining completeness and relevance is of extremely complex, especially in the context of outsourcing communication [17,27]. This is an interesting finding calling for future research to explore more deeply in this direction.

6.2. Theoretical contributions

This study, like many other research endeavors, yields several contributions. First, its findings extend the emerging literature on live chat usage in online markets. The emerging literature has revealed the signaling function of affective and informative interactions on purchase decisions within live chat [23,37], which laid a good foundation for the development of this paper. However, upon a deeper exploration of this dynamic domain, a critical research gap is discerned that warrants our attention—the nuanced influence of live chat's affective and informative signals and the moderating role of consumers' prior experience in purchase decisions. The importance of prior experience cannot be overstated in our comprehension of live chat interactions, as it plays a pivotal role in how consumers perceive and prioritize various signals during the communication process. The undertaking of this study extends our knowledge about how prior experience influences different types of signals in live chat interactions. Specifically, our research reveals that the experienced consumer would value informative signals (e.g., the information quantity), whereas a naive consumer would pay more attention to affective signals (e.g., politeness and sentiment valence).

Second, this paper contributes to signaling theory in two ways. On one hand, past studies have attempted to apply signaling theory in various research streams [1,35], but have not paid for live chat. This study extends signaling theory by mining how informative and affective signals in live chat work together to influence decisions. On the other hand, signaling theory assumes the important role of signaling, but the intensity of these signals may be heterogeneous. As the previous literature stated, receivers are boundedly rational and cannot focus equally on all available signals [47,64]. This study reveals the different preferences of individual characteristics in the process of signal reception, as well as different mechanisms aroused by these two-dimensional signals (i.e., informative and affective), by investigating the moderating effect of prior experience.

Third, this paper is one of the preliminary studies that provide insights into how live chat influences service transactions in OOPs. As an emerging market, OOPs reduce search and transaction costs. However, due to the highly customized and semianonymous nature of service transactions, the issue of information asymmetry between the consumer and the service provider inevitably arises. Although published studies have focused on mechanisms that mitigate asymmetric information, such as reputation [4,12,26] and dispute resolution [8], the role of live chat has been largely underexplored. A service product is co-created by service providers and consumers, which requires continuous interaction between different sides of the market [17,32]. Thus, as a computer-mediated communication medium, live chat plays a crucial role in online service transactions. This paper contributes to this research stream by empirically exploring the decisions made by consumers after live chat communication.

6.3. Practical implications

Through understanding the effect of the signals in live chat content on consumers' purchase decisions, service providers should seriously consider how to leverage signals effectively to promote the completion of a transaction. The results show that both informative signaling (e.g., the information quantity and response timeliness) and affective signaling (e.g., politeness and sentiment valence) can contribute to a consumer's purchase decision. Thus, service providers should recognize the importance of the wording used in live chat communications, while affirming and encouraging the needs and ideas of users. These positive affective signals help consumers have a pleasant shopping experience and improve their desire for further communication and purchases. In addition, service providers should convey rich and comprehensive information to consumers, thus helping to reduce uncertainty. When receiving an inquiry from consumers, service providers should respond to them as quickly as possible; a timely response can immediately solve their particular problems before ambiguity results in a negative effect.

For platform operators, it is necessary to improve the performance of the live chat function further to ensure that consumers can contact service providers in time when consulting, in order to promote subsequent interactions and online transactions. Specifically, the platform operators should make the following efforts: First, the current design of the live chat is a passive trigger mode; that is, the service provider can interact with the consumers only if a request is initiated by the consumer [59]. Considering the importance of live chat in promoting outsourcing service transactions, a proactive live chat may be a useful way for service providers to identify potential consumers [31]. Second, because politeness and sentiment are tightly associated with linguistic features in text semantic mining [18], the platform operators should develop a real-time semantic analysis tool to enable service providers to grasp the use of their affective signaling (such as politeness and sentiment) in time. Third, when consumers send messages to service providers, strong reminders should be set to ensure that the latter can respond in a timely manner.

Consumers' prior experience can shape their preferences, so that they have stronger goal-directed behavior and greater appreciation for informational value [43]. In reality, service providers on outsourcing platforms are not aware of the importance of consumers' prior experience. On the contrary, all consumers are treated as roughly the same, without realizing that differences in experience may lead to differentiated preferences. The results show that prior experience negatively moderates the influence of affective signaling (e.g., politeness and sentiment) on purchase decisions, while it positively moderates the influence of informative signaling (e.g., information quantity). If service providers communicate with experienced consumers through live chat, then providing a high information quantity may be more effective than using affective signaling. However, in cases where consumers have less experience, the emphasis on using affective signals (e.g., politeness or sentiment) should be strengthened, and the effect of the information quantity can be downplayed. Thus, appropriate and effective guidance can help service providers choose suitable signals during live chat communication, thereby facilitating online transactions. In addition, platform operators can develop a function that can display consumer-related information (such as past purchase volume and length of use) near the live chat box, without infringing on the privacy of consumers, so that service providers can choose appropriate signals.

CRediT authorship contribution statement

Lingfeng Dong: Formal analysis, Funding acquisition, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Zhongsheng Hua:** Conceptualization, Funding acquisition, Supervision. **Liqiang Huang:** Conceptualization, Funding acquisition, Investigation, Supervision, Writing – original draft, Writing – review & editing. **Ting Ji:** Conceptualization, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing. **Fengxin Jiang:** Formal analysis, Investigation, Methodology. **Guangzhu Tan:** Data curation, Investigation, Software, Supervision. **Jie Zhang:** Conceptualization, Funding acquisition, Methodology, Writing – review & editing.

Appendix. Comparison of relevant literature on live chat

Source	Context	Theoretical basis	Main findings	Research Gap Affective signal	Informative signal	Moderating effect of prior experience
MIS Quarterly [45]	E-commerce	Media synchronicity theory	The effective use of instant messenger, message box and feedback system can influence interactivity and presence.	×	×	×

(*continued on next page*)

(*continued*)

Source	Context	Theoretical basis	Main findings	Research Gap Affective signal	Informative signal	Moderating effect of prior experience
Thirty Seventh International Conference on Information Systems [58]	E-commerce	Two-stage choice model	The usage of live chat influences purchase decisions	×	×	×
Computers in Human Behavior [38]	Mobile phone networks	Information system success model	☐ Reliability and assurance influence perceived information quality ☐ Empathy and responsiveness influence perceived wait time. ☐ Empathy influence satisfaction with the experience.	√	√	×
Electronic Commerce Research and Applications [37]	E-commerce	Telepresence theory, uncertainty reduction theory	☐ The usage of live chat influences purchase decisions ☐ Frequency and speed are associated with purchase decision.	×	√	×
Information Systems Research [59]	E-commerce	Information cascade theory	☐ The usage of live chat can promote consumer's purchase decision. ☐ The live chat use positively moderates the relationship between sale and purchase decision ☐ The live chat use negatively moderates the reputation between sale and purchase decision	×	×	×
Journal of the Association for Information Science and Technology [23]	Shopping websites	Speech act theory	☐ The positive affect term has an influence on purchase conversion. ☐ The positive emoticon and negative affect term of retailer have an influence on purchase conversion. ☐ The message count of the shopper and retailer has an influence on purchase conversion.	√	√	×
Information Systems Research [18]	Online labor markets	Politeness theory	Politeness has a positive effect on hiring.	√	×	×
Production and Operations Management [57]	E-commerce	Functional theory in persuasion,	Live chat has a positively effect on conversion rate.	×	×	×
Journal of Operations Management [21]	Income tax filing software	Attribution Theory	☐ The waiting time a customer experiences during a live chat contact center interaction can alter the speed the customer acts within service.	×	√	×

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