



Article

Livestream Assistants as Moderators: Dual Pathways of Emotional Contagion and Cognitive Reinforcement in E-Commerce Livestream Consumer Interactions

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Abstract

Focusing on the dual pathways of emotional contagion and cognitive reinforcement, this study explores consumer interaction mechanisms in e-commerce live streaming and investigates the moderating role of live streaming assistants. Using valid real-time panel data spanning 4671 min across 40 Taobao Live sessions, this research adopts the LIWC-based text mining approach to extract indicators of user emotional expression and cognitive expression from bullet comments and matches minute-level multi-source data for empirical analysis. The empirical results indicate that early emotion expression and cognitive expression are significantly associated with intertemporal reinforcement patterns, with emotional contagion being more closely linked to instant purchase decisions and cognitive reinforcement being more closely linked to user follow behavior. While assistant intervention is associated with a more active overall interaction atmosphere across the two psychological pathways, it is negatively correlated with product sales, suggesting a dual-edged association. By introducing human assistants into the analytical framework and empirically distinguishing differentiated outcome associations related to emotional and cognitive mechanisms, this study extends the application of consumer-behavior theories to real-time livestream interaction contexts and offers cautious practical implications for livestream operation and assistant deployment.

Keywords: e-commerce live streaming; livestream assistants; emotional contagion; cognitive reinforcement



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1. Introduction

Social interaction serves as the cornerstone of the e-commerce live streaming ecosystem. It encompasses the “parasocial interaction” between streamers and users, transforming one-way information transmission into two-way emotional connections. Top influencers on major platforms have evolved into Internet celebrities, driving significant economic value [1]. Beyond this dyadic streamer–user dynamic, social interaction in e-commerce live streaming also entails consumer-to-consumer engagement. Within live streams, real-time interactions such as bullet comments, follows, and likes not only facilitate information exchange but also foster collective emotional contagion through social proof mechanisms—ultimately shaping consumer behavior [2]. For example, enthusiastic early comments (e.g., “Just placed my order!”) exert a contagious influence on subsequent viewers, triggering conformity tendencies and expediting purchase decisions. A McKinsey report highlights

that the interactivity of livestream e-commerce, including chat functionalities and real-time feedback, represents a key differentiator from traditional e-commerce models and contributes 10–20% of overall e-commerce sales growth [3].

Cognition and emotion constitute two critical pathways in users' information processing, both of which have been shown to significantly influence user behavior [4]. Cognition refers to the process of understanding phenomena, acquiring knowledge, and processing information, while emotion encompasses attitudes and internal experiences that evaluate the relationship between objective phenomena and subjective needs [5]. Existing research generally adopts the Cognition–Affect–Behavior (CAB) model to explain the emotional and cognitive processing mechanisms in users' decision-making processes. The CAB model was initially conceptualized by Bagozzi (1982), who empirically demonstrated that individuals' cognitive evaluations generate affective states, which in turn shape behavioral intentions and actual actions [6].

Live streaming interactions are replete with cognitive and emotional information. Scholars primarily investigate consumer responses and underlying mechanisms through questionnaire-based studies [7,8]. However, user emotions expressed via bullet comments propagate dynamically as live streaming sessions unfold, and retrospective questionnaire-based data are unable to capture these real-time emotional fluctuations or the evolving trajectories of cognitive reinforcement. This notable research gap has contributed to a paucity of empirical studies investigating the dynamic interplay between cognitive and emotional processing pathways within e-commerce live streaming contexts. In response to this limitation, recent methodological advances have highlighted the value of automated text mining to extract psychological constructs from unstructured user-generated content [9]. Such approaches enable researchers to quantify real-time cognitive and emotional expressions from natural language data, thereby capturing the dynamic nature of user experiences during live interactions.

The massive volume of real-time interactions imposes significant response pressure on streamers, who typically struggle to address every consumer comment and question individually. To mitigate the mismatch between streamers' limited service capacity and surging consumer demand, some live streaming platforms have introduced assistants to support sales operations. Existing literature has broadly categorized livestream assistants into two types based on their functional attributes. The first type comprises information technology assistants, who primarily support live streaming through technical tools including image processing, text mining, and data analysis software [10]. The increasingly popular AI assistants in recent years also fall into this category; they mostly provide automated responses in the form of online customer service, helping to improve information processing efficiency and reduce consumer uncertainty [11]. The second type consists of human assistants who directly participate in livestream interactions: one subgroup consists of on-screen co-streamers who assist in product introductions and play a collaborative live streaming role; the other subgroup consists of bullet comment moderators or room controllers, who are responsible for guiding comment atmosphere, answering user questions, monitoring bullet comment content, and conducting risk management. Although both types of assistants play important roles in the livestream ecosystem, research has shown that consumers exhibit significantly higher trust in human assistants than in intelligent technical assistants [12].

To date, academic discussions on information technology assistants have been relatively comprehensive, yet empirical research on how human assistants intervene in live streaming and the effects of such interventions remains limited. Existing studies have mostly focused on technology-driven auxiliary functions, with few in-depth explorations of the specific intervention behaviors of human assistants in bullet comment interactions [10].

Compared with technical assistants, human assistants' behaviors are characterized by greater flexibility, randomness, and context dependence, which makes their impact mechanisms more difficult to predict. When examining the mechanisms of emotional contagion and cognitive reinforcement in live streaming, existing literature has generally overlooked the moderating role of human assistant intervention frequency, leading to an incomplete explanation of interaction dynamics and performance changes in real livestream rooms. Therefore, systematically investigating the intervention role of human livestream assistants and their impact pathways holds important theoretical and practical value.

Based on the above background and research gaps, this study aims to examine the mechanism of consumer interaction in e-commerce live streaming, with a focus on the dual processes of emotional contagion and cognitive reinforcement. To fulfill this aim, we formally propose the following research questions:

- (1) Do emotional contagion and cognitive reinforcement patterns exist in user interactions during e-commerce live streaming? How are these two patterns associated with live streaming performance (i.e., product sales and user follow behavior)?
- (2) How does the intervention behavior of livestream assistants moderate the above emotional contagion and cognitive reinforcement patterns, and how is it associated with live streaming performance?

To advance this line of research, we collected 4685 min of real-time bullet comment data and transaction records from 40 live streaming sessions on Taobao Live. Leveraging text mining techniques, we extracted emotion expression and cognitive expression from consumers' bullet comment interactions. These extracted components were integrated with minute-level live streaming metrics to construct a fixed-effects model. This model examined the presence of cognitive reinforcement and emotional contagion patterns in e-commerce live streaming interactions, while further analyzing the associations between these two patterns and two key performance indicators: product sales and user follow behavior. Additionally, we analyzed how assistant intervention frequency during live streaming sessions is related to emotional contagion and cognitive reinforcement patterns, thereby refining the analytical framework for live streaming operation management.

This study makes two main contributions. First, it extends the CAB perspective to the real-time context of e-commerce livestreaming. While prior CAB research has often relied on static or survey-based designs, this study uses minute-level livestream data to examine how users' cognitive and emotional expressions show temporal continuity and mutual association in natural interactions. It further links these two pathways to distinct behavioral outcomes, showing that emotional expressions are more closely associated with immediate purchases, whereas cognitive expressions are more closely associated with follow behavior. In this way, the study provides a contextual extension of both the CAB framework and dual-process perspectives in livestream commerce. Second, this study introduces human livestream assistants into the user interaction–performance framework and treats assistant intervention frequency as an observable moderator of cognitive and emotional pathways. The findings suggest that assistant intervention frequency is positively associated with the temporal continuity of both emotional contagion and cognitive reinforcement patterns, while being negatively related to sales performance. These findings provide a more nuanced understanding of how human assistant participation is related to consumer interaction dynamics and performance outcomes in e-commerce livestreaming.

The remainder of the paper is organized as follows: First, we present the theoretical foundation and review existing literature. Next, we propose research hypotheses. Subsequently, we describe the methodology and empirical findings. Finally, we discuss key discoveries, theoretical contributions, and practical implications.

2. Theoretical Foundations and Literature Review

2.1. Cognition–Affect–Behavior (CAB) Model

The CAB model is a classic social–psychological model of consumer attitudes, which posits that attitudes consist of three interrelated components: cognition, affect, and behavior [13]. The cognitive component represents an individual’s knowledge, opinions, or beliefs, which can be manifested in specific contexts as psychological capital characteristics such as consumers’ emotional intelligence [14]. The affective component involves explicit emotional responses, often associated with experiences such as satisfaction [15]. The behavioral component reflects an individual’s predisposition to take specific actions, such as continuous usage intention or loyalty [15]. Regarding their interrelationships, cognitive evaluations elicit affective responses, which further shape behavioral intentions. Meanwhile, complex interactions exist among affect, behavior, and other factors. Cognition and emotion do not exist independently but interact with each other, and an individual’s attitude is jointly shaped by these three sequentially linked components.

In the context of e-commerce and digital consumption, the CAB framework serves as a core theoretical lens for interpreting consumer behavior, as it delineates how consumers make purchase decisions [16]. Specifically, in the retail service sector, this model has been applied to measure service delivery across actual stages of customer experience, encompassing cognitive, emotional, and behavioral responses [17]. This implies that consumer decisions can be deconstructed into a sequential process from cognitive evaluation to emotional reaction and finally to behavioral intention [18]. Therefore, in social cue-rich environments such as e-commerce live streaming, the CAB framework enables a systematic analysis of the complete psychological process through which viewers progress from observing content, developing emotional resonance, to making consumption decisions [19].

Live streaming e-commerce represents a highly dynamic, real-time interactive context where frequent interactions among viewers, hosts, and platforms are closely related to consumers’ cognitive and emotional responses. Traditional CAB models typically follow a static, linear, and unidirectional causal logic, which cannot adequately capture or explain the dynamic, reciprocal, and continuously evolving relationship between cognition and emotion in live streaming. Furthermore, the three components of the traditional framework are often difficult to distinguish empirically and tend to oversimplify the complex, intertwined nature of attitude formation. To address these gaps, this study regards cognitive expression and emotion expression as a mutually associated system and uses high-frequency, real-time panel data to examine their temporal associations in livestream interactions. By doing so, this paper applies the CAB framework to a dynamic livestream context and provides empirical evidence for understanding consumer psychology and behavior in real-time interactive media environments.

2.2. Emotional and Cognitive Information in Live Streaming

Both emotional and cognitive information are present in live streaming contexts, where they may interact and mutually influence each other synchronously [20]. Lazarus (1982) proposed Cognitive Appraisal Theory (CAT) [21]. Its core proposition is that individuals continuously form sophisticated cognitive appraisals based on the relevance of events to their personal well-being, and these appraisals determine the emotions individuals experience as well as the coping strategies they adopt. For instance, in emotional tasks, emotional conflicts (e.g., positive vocabulary paired with negative expressions) activate cognitive regions, while in cognitive tasks, task performance outcomes also affect participants’ emotional states [22]. Beyond the reciprocal influence between emotion and cognition, existing research has also identified self-reinforcing effects within each domain.

Hatfield et al. (1993) proposed emotional contagion theory, which states that emotion can be transmitted from one individual to another, and emotional contagion refers to the process by which individuals achieve unconscious or conscious emotional convergence [23]. Streamers can trigger emotional mimicry in users through symbolic expressions such as vocal tone intensification, micro-expression amplification, and dramatic body language, thereby achieving interpersonal emotional synchronization [24]. Consequently, streamers' performances can stimulate consumer emotions, enhancing their willingness to purchase recommended products [25]. In addition to streamers infecting users' emotions through symbolic expressions, real-time bullet comments posted by users can also facilitate emotional contagion. When users perceive collective emotional tendencies, cognitive dissonance pressure drives them to align their own emotions, forming a pattern where emotions spread gradually from one user to others [23]. Visual indicators, such as likes and interaction frequency, serve as social proof cues, further amplifying the potential for group polarization. Moreover, this peer-to-peer emotional contagion often exhibits stronger emotional amplification effects than streamer-driven contagion [26].

Cognition refers to the individual process of acquiring knowledge or processing information, which is the psychological activity that follows information exposure and exerts a significant influence on information behavior. Cognitive reinforcement effects are equally present in live streaming contexts. Existing research indicates that informational content within consumer interactions significantly boosts traffic, with interaction volume and participant numbers partially mediating the impact of consumer engagement on sales performance [26]. Higher perceived information value reduces time and effort costs, thereby enhancing perceived value during the shopping process [27]. However, other studies reveal that consistency in the content and format of consumer interactions negatively affects purchase intention, driven by two psychological mechanisms: resistance and information richness [28].

The Elaboration Likelihood Model (ELM) suggests that consumers do not process persuasive information through a single mechanism, but elaborate information to different degrees through the central and peripheral routes depending on their involvement, motivation, and ability to process information [29]. Through the central route, users evaluate substantive message cues such as argument quality, information relevance, comprehensiveness, usefulness, and credibility, which makes this route especially relevant for explaining cognitive words, information judgments, and relatively deliberate behavioral responses such as following behavior in livestream comments [30,31]. Through the peripheral route, users are more likely to rely on non-content cues such as source credibility, social proof, interaction atmosphere, and emotional expression, which makes this route useful for explaining emotional expression, emotional contagion, and more immediate affective responses such as impulsive purchase decisions in livestreaming contexts [31,32]. In the livestreaming context of this study, cognitive expressions can therefore be understood as closer to central-route information processing, whereas emotional expressions and social atmosphere are closer to heuristic cues in the peripheral route, jointly explaining how cognitive reinforcement and emotional contagion operate in parallel within user interactions [31,32].

To measure users' cognitive and emotional expressions, the most accessible text analysis approach is the dictionary-based, top-down method, for which LIWC is the most widely used tool. LIWC contains a set of word lists, many of which are developed based on psychological scales. Specifically, LIWC's measurement of emotion is grounded in the PANAS scale [33], and its key dimensions include positive emotion, negative emotion, anxiety, anger, sadness, positive tone, negative tone, and swear words. Cognition has been incorporated as a general category that reflects how people think or refer to their thoughts.

It serves as an overarching dimension that includes subcategories such as all-or-none thinking, cognitive processes, and memory. ShabbirHusain et al. (2024) employed the LIWC dictionary to quantify four types of linguistic characteristics (drive words, cognitive language, emotional language, and conversational language) from Fintech brands' tweets [34]. Results show that drive and cognitive language enhance consumer engagement via the central route, while emotional and conversational language boost engagement through the peripheral route of the Elaboration Likelihood Model.

Research has confirmed emotional contagion and cognitive reinforcement in live streaming, but nearly all studies treat them as independent processes. Few studies examine how they dynamically interact or how their mutual association evolves over time. This study is among the first to treat cognitive and emotional processes as a coupled dynamic system and to examine their real-time reciprocal reinforcement.

2.3. Social Interaction

Social interaction refers to interpersonal activities or relationships between individuals and others, encompassing communication, conflict, competition, and related phenomena [35]. Unlike offline interactions, media figures convey messages to audiences through intermediaries in online or media contexts. Within this interactive framework, viewers respond to media figures as if they were real individuals, fostering a sense of "face-to-face" engagement. This virtual social interaction, distinct from everyday offline interactions, is termed quasi-social interaction or parasocial interaction [36]. Importantly, quasi-social interaction is a unidirectional construct: audiences perceive certain cues from media figures as attempts to engage them in dialogue. However, media figures do not target specific audiences, and audience responses may not be acknowledged by the former [37]. Research indicates that the emergence of social interaction is shaped by both contextual factors—such as platform characteristics and interaction modalities [38]—and the characteristics of the interacting parties, including attitude homogeneity and attractiveness [39]. Furthermore, social interaction influences the formation of consumers' social ties, which directly impacts subsequent marketing-related performance metrics, such as brand reputation, purchase intention, and impulsive buying [40,41].

In the context of e-commerce live streaming, social interaction manifests primarily through streamer–consumer engagement. Streamers exhibit diverse attributes, including expertise, attractiveness, credibility, interactivity, and recognition, with different streamer types being suited to distinct product categories and sales strategies [42–44]. Furthermore, streamers can develop interaction strategies from multiple dimensions, namely process, content, and social dynamics, to enhance the effectiveness of social interaction and achieve superior live streaming performance [45]. Social interaction in e-commerce live streaming also manifests through consumer-to-consumer influence. Within livestream sessions, real-time comments serve as the primary medium for consumer interaction. Through these interactions, consumers exchange product information, which mitigates information asymmetry and facilitates purchasing decisions. Additionally, debates and emotional arousal in consumer interactions heighten audience excitement, thereby influencing purchasing or social behaviors [46]. Several studies indicate that real-time interactions during live streaming are more complex than those on traditional social media, with certain interactions potentially causing consumer purchase hesitation [47].

Research has established the importance of social interaction in live streaming, but it remains largely descriptive. Few studies explain how social interactions are associated with the dynamic coupling of emotion expression and cognitive expression over time. This study explicitly links social interaction to the dynamic evolution of cognitive–emotion states, providing a more process-based explanation of viewer engagement.

2.4. Assistant Behavior in Online Platforms

Åberg and Shahmehri (2000) pioneered the “web assistant” concept, emphasizing the critical role of human assistants in e-commerce scenarios: specifically, delivering personalized services through real-time communication to offset the limitations of automated systems [48]. They proposed a human–computer collaboration framework, recommending the integration of live human assistants into e-commerce platforms to provide real-time user support via channels such as chat windows and phone calls. Additionally, this framework suggests dynamically adjusting the weighting between human and automated services based on contextual factors [48].

Extensive research has compared the roles of human and computer assistants. Findings indicate that consumers exhibit significantly greater trust in human services than in machine-based alternatives, particularly during complex decision-making processes involving products such as financial services [49]. Human assistant interventions mitigate perceived risk, as human agents are capable of delivering explanatory guidance, engaging in interactive dialogue, and assuming clear accountability. These are attributes that automated systems frequently lack. Furthermore, many users experience technological anxiety or unfamiliarity with digital interfaces, highlighting the need for flexibility in online store design. This flexibility should be realized through the integration of diverse interaction modalities (e.g., natural language communication, hypertext browsing) and information service tools (e.g., recommendation systems, search engines). Such integration enables users to select the most appropriate interaction approach based on personal preferences or immediate needs [48].

Livestream assistants occupy a pivotal role within the e-commerce live streaming ecosystem. Streamers are constrained by inherent time and capacity limitations that impede their ability to manage real-time audience interactions and address user inquiries, even as consumers increasingly expect immediate, personalized responses. Wang et al. (2025) [11] found that AI live streaming assistants reduce consumer uncertainty by facilitating information acquisition and processing through chat-based interactions, and although they may occasionally disrupt purchasing decisions, their overall net value remains positive.

Beyond information support, assistants perform critical operational and relational functions. They monitor comment sections in real time to filter inappropriate content, preventing streamers from being distracted by negative remarks. When streamers experience emotional fluctuations, assistants adjust the broadcast atmosphere to ensure a smooth stream flow. Additionally, assistants collect user feedback (e.g., product preferences, livestream suggestions) to provide data-driven support for streamers, nurture long-term relationships within fan communities, and enhance user stickiness through regular interactive engagement [50]. Thus, assistants fulfill a multifaceted role in e-commerce live streaming: they serve as strategy executors, crisis managers, and image guardians for streamers, while acting as service providers, emotional connectors, and demand analysts for users.

Assistants support information delivery and interaction management, but no existing work examines how assistant behavior moderates the dynamic cognitive–emotion system over time. This study is the first to model assistant behavior as a moderator of the dynamic cognition–emotion reciprocal system, which may advance both theory and practice.

3. Hypothesis Development

User emotion expression refers to the valenced emotional cues expressed by users in real-time interactions [47]. In real-time e-commerce livestreaming, user interactions create situational stimuli that may shape the dynamic transmission of emotional states. According to emotional contagion theory, individuals may mimic and synchronize with others’ emotional expressions, behaviors, and postures, thereby contributing to the convergence of

affective states within a group [23]. In the interactive context of livestreaming, early users may generate salient emotional cues through bullet comments, likes, and synchronized reactions to time-limited promotions, which together shape the emotional environment of the livestream room [2]. These collective expressions may strengthen users' social identification with the livestream room and increase conformity-oriented responses, thereby facilitating emotional contagion among viewers [25]. Through this contagion process, early-stage user emotion expression may be associated with later-stage user emotion expression by sustaining the temporal continuity of affective cues in livestream interactions. Based on the above reasoning, we propose the following hypothesis:

H1a. *Early-stage user emotion expression in e-commerce live streaming is positively associated with later-stage user emotion expression.*

Cognitive expression is the extent of elaborate and systematic information processing [51]. In e-commerce livestreaming, later users often enter the stream with limited product information and uncertainty about product quality, deal reliability, and purchase relevance. Under such uncertainty, early users' product-related questions, evaluations, and explanations provide visible informational cues for subsequent viewers [49]. Drawing on informational social influence and social learning perspectives, later users may rely on these observable cues to interpret product information and form their own evaluations [50]. As product-related questions, explanations, and evaluations accumulate, they increase the salience of informational cues and guide the interaction focus toward product assessment and decision-related discussion [51]. Therefore, early-stage cognitive expression may encourage later users to share more cognition-related content, reflecting the cumulative reinforcement of informational cues in livestream interactions. Based on the above reasoning, we propose the following hypothesis:

H1b. *Early-stage user cognitive expression in e-commerce live streaming is positively associated with later-stage user cognitive expression.*

During the inter-consumer emotional contagion process in e-commerce live streaming, emotions expressed by early users gradually spread and exert influence on the emotional states of subsequent viewers. When assistants participate in consumer interactions via bullet comments, they can highlight critical user comments, regulate interaction rhythm, and enhance the visibility and consistency of early emotional signals, thereby enabling later viewers to more easily capture and resonate with emotional cues conveyed by early users [52,53]. In addition, assistants can direct the flow of discussions and suppress irrelevant or disruptive content that may interfere with emotional contagion, allowing this process to proceed more smoothly and continuously [54]. Accordingly, we posit that livestream assistant intervention frequency amplifies the strength of emotional contagion from early-stage to late-stage users, rather than directly generating new emotional stimuli. In summary, we propose the following hypotheses:

H2a. *Assistant intervention frequency in e-commerce live streaming positively moderates the association between early-stage and later-stage emotion expression.*

During e-commerce live streaming interactions, early users' product-related cognitive expressions tend to consolidate and influence later users' rational understanding and judgments. Livestream assistants reinforce this process by organizing interactive focus, answering product-related questions in a timely manner, and guiding discussion toward product-related topics [48]. By centering interactions on product information and key

user opinions, assistants strengthen the continuity and salience of early cognitive signals, helping later viewers better perceive and accept the rational cues formed by initial users. Therefore, we propose the following hypotheses:

H2b. *Assistant intervention frequency in e-commerce live streaming positively moderates the association between early-stage and later-stage cognitive expression.*

In e-commerce livestreaming, purchase and follow behaviors represent two distinct forms of consumer response. Purchase behavior is a short-term transactional response that is often made under time pressure and is more likely to be associated with immediate affective cues, such as excitement, urgency, and emotional contagion [55]. By contrast, follow behavior is a lower-cost but longer-term relational response, which reflects users' willingness to maintain future interaction with the streamer or livestream room [56]. This behavior is more likely to depend on cognitive evaluation, perceived informational value, and expectations of continued usefulness.

On the emotional pathway, early user emotion expression may create an affective atmosphere that is associated with spontaneous and immediate consumer responses [6]. Research on impulse buying suggests that emotional contagion in e-commerce livestreaming is closely related to unplanned purchase behavior [55]. Enthusiastic comments, lively atmospheres, and time-limited promotional cues may increase users' emotional arousal and sense of urgency, making purchase behavior more likely in the short term [1,2]. Accordingly, we propose:

H3a. *Early-stage user emotion expression in live streaming is positively associated with users' purchasing behavior.*

On the cognitive pathway, early user cognitive expression provides product-related information, evaluations, and explanations that may reduce uncertainty and increase perceived informational value [27]. Compared with immediate purchase behavior, follow behavior reflects a more relational and future-oriented form of engagement. Users may follow the streamer or livestream room when they perceive that the interaction provides useful product information, reliable explanations, or continued decision support [26]. Therefore, cognitive expression is more likely to be associated with follow behavior, as it helps users form expectations about the long-term informational value of the livestream room [57]. Accordingly, we propose:

H3b. *Early-stage user cognitive expression in live streaming is positively associated with users' follow behavior toward streamers.*

In summary, the conceptual model of this study is illustrated in Figure 1.

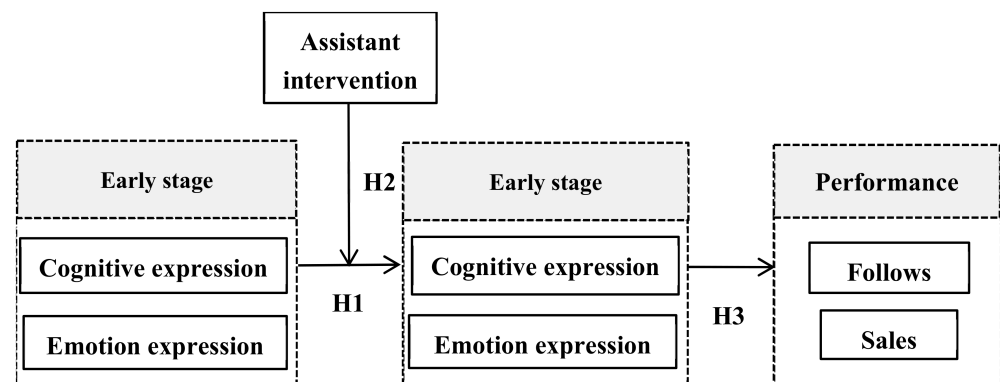


Figure 1. Conceptual Model.

4. Research Methodology

4.1. Data Collection

This study collected real-time interaction and performance data from two livestream rooms on Taobao Live, one of the largest e-commerce live streaming platforms in China. The two livestream rooms are operated by different streamers and focus on daily necessities with stable market demand, which helps ensure the representativeness of typical e-commerce live streaming scenarios. Both livestream rooms are hosted by different streamers to reduce biases driven by individual streamer characteristics.

Data were collected during December 2024, covering 40 complete live streaming sessions with a total valid observation window of 4671 min (approximately 78 h). The initial raw data volume was 4685 min, with 14 min excluded during data cleaning due to temporary store technical glitches.

Bullet comments were collected via web crawling using a customized Python 3.10-based crawler. The crawler integrated Selenium and Requests libraries to simulate real-user access to the target live streaming rooms, capture real-time bullet comments in HTML DOM structure, and distinguish between consumer and assistant comments based on Taobao Live's built-in user identity tags (assistant accounts are marked with an "Assistant" badge in comment metadata).

Real-time product sales, live streaming room follower counts, fan group counts, and real-time viewership were obtained through authorized access to the store's backend data system. These metrics are recorded automatically by Taobao Live's official system.

To align the temporal resolution of heterogeneous data types, we integrated bullet comment data and performance/operational data based on time stamps. Specifically, all second-level bullet comments were aggregated into minute-level bins. The aggregated minute-level comment data were matched one-to-one with the minute-level performance/operational metrics via their shared minute-level time stamps, forming a unified panel dataset with consistent temporal granularity.

4.2. Measurement and Descriptive Statistics

4.2.1. Measures

The independent variable is user interaction, which is further categorized into two dimensions: customer emotion expression and customer cognitive expression. These two sub-dimensions were measured via text mining of consumers' real-time bullet comments. Customer emotion expression and customer cognitive expression were extracted from users' real-time bullet comments using the Linguistic Inquiry and Word Count [58]. We used the most recent version of the widely validated text analysis software (LIWC-22). LIWC-22 includes a built-in simplified Chinese dictionary specifically developed and validated for contemporary Chinese online discourse, which enables direct and reliable measurement of emotional and cognitive linguistic features without additional adaptation [59].

Prior to LIWC analysis, all Chinese bullet comments were processed using Jieba segmenter (<https://github.com/fxsjy/jieba>, accessed on 16 July 2026), a standard and robust Chinese word segmentation tool widely used in social media and live streaming text research. Word segmentation is a necessary preprocessing step for Chinese text, as it divides continuous character strings into meaningful lexical units for accurate dictionary matching.

Customer emotion expression was measured using the Emotional Tone dictionary in LIWC-22, which captures overall positive versus negative emotional valence in the text. Customer cognitive expression was measured using the Cognitive Process dictionary in LIWC-22, which includes words related to insight, causation, certainty, and reasoning, reflecting users' rational information processing and evaluative judgments. To strengthen

theoretical justification, we clarify the theoretical connection between LIWC cognitive lexicon and actual cognitive expression in the livestream context. Words denoting insight, causation, certainty, and reasoning correspond directly to viewers' efforts to understand, evaluate, and judge product information in real time. These terms reflect deliberate cognitive processing of promotional content, rather than superficial linguistic patterns, thereby meaningfully capturing viewers' cognitive expression. All measures were computed as the relative percentage of emotional and cognitive words within total words per minute to ensure comparability across time intervals.

To ensure the construct validity of the LIWC-derived measures, we conducted a human coding verification: 1200 randomly selected bullet comments were independently rated by two trained coders using 7-point scales for emotion expression (1 = strongly negative to 7 = strongly positive) and cognitive expression (1 = low to 7 = high) based on LIWC's operational definitions. The inter-coder reliability met rigorous standards (Cronbach's alpha: 0.87 for emotion expression, 0.85 for cognition expression; Cohen's kappa: 0.81 for emotion expression, 0.79 for cognition expression), and Pearson correlation analysis confirmed strong convergent validity—LIWC-derived emotional ($r = 0.78, p < 0.01$) and cognitive word proportions ($r = 0.75, p < 0.01$) correlated significantly with human ratings.

The dependent variable in this study is livestream performance, which is primarily operationalized using two key metrics: product sales and the number of livestream followers. To address potential endogeneity issues and ensure the robustness of empirical results, this study incorporates three categories of control variables: product characteristic factors, including product price, product category (coded as 1 for search goods such as detergents and 0 for experience goods such as personal care products) and discount (whether the live falls during the Double 12 promotion period); streamer factors, including streamer gender (coded as 1 for female and 0 for male) and livestream duration; and social factors, including volume of consumer interaction, fan club size and livestream viewership. All data utilized in this study have undergone statistical processing and are aggregated at the minute-level to accurately capture the dynamic changes in livestream interactions and performance during the observation period.

4.2.2. Descriptive Statistics

Table 1 reports the descriptive statistics for all variables included in this study. The mean value of product sales is 2.805, with a corresponding standard deviation of 4.969. This pattern indicates that product sales generated during livestream sessions display substantial volatility and may be related to livestream operational strategies or consumer interaction dynamics. The mean follower count is 2.124, paired with a standard deviation of 2.077, suggesting that fluctuations in consumer follow behaviors are less pronounced than those observed in purchasing behavior.

In addition, both customer emotion expression and cognitive expression yield low mean values and small standard deviations. These results reflect the overall stability of these two metrics, with minimal variability recorded across the observation period. The mean customer interaction count is approximately 3.33, yet its standard deviation surpasses the mean value. This finding implies that although the livestream sessions maintained a baseline level of audience engagement, customer interaction intensity varied considerably across different time segments, with certain intervals exhibiting unusually high levels of activity.

Finally, the mean assistant interaction count is 0.464, with a standard deviation of 0.643. This outcome suggests that assistant participation during livestreams was not continuous or real-time; instead, such interactions were initiated only when deemed necessary.

Table 1. Descriptive Statistics for Each Variable.

Variable	Measures	Mean	SD	Min	Max
Dependent Variable					
Sales	Product sales per minute	2.805	4.969	0	79
follows	Number of consumer follows to the livestream room per minute	2.124	2.077	0	28
Independent Variable					
emotion	Proportion of emotion-related words in livestream bullet comments per minute	0.035	0.066	0	0.5
cognitive	Proportion of cognition-related words in livestream bullet comments per minute	0.110	0.121	0	0.816
Moderating Variable					
inter_a	Number of livestream assistant bullet comments per minute	0.464	0.643	0	4
Control Variable					
price	Price of the focal product being livestreamed (RMB)	53.927	55.414	9.9	445.9
category	product_category (1 = search goods, 0 = experience goods)	0.589	0.492	0	1
discount	Double 12 promotion (1 = yes; 0 = no)	0.288	0.453	0	1
gender	Streamer gender (1 = female; 0 = male)	0.711	0.454	0	1
duration	Total live stream duration (minutes)	225.806	189.483	1	850
inter_c	Number of consumer bullet comments per minute	3.326	4.411	0	38
fans	Number of fan groups in the livestream room per minute	0.324	0.920	0	31
views	Number of viewers in the livestream room per minute	377.945	242.990	12	1668

4.3. Model Specification

We consider a fixed-effects panel model to estimate minute-level temporal associations in e-commerce livestreaming. The dataset consists of minute-level observations, which allows us to observe how user emotion expression, cognitive expression, assistant intervention frequency, and performance outcomes co-vary over time within real livestream contexts. Because the empirical focus is on within-context temporal dynamics rather than broad between-room heterogeneity, the fixed-effects specification is used as the main modeling strategy. This approach helps account for time-invariant unobserved heterogeneity across livestream sessions, such as stable differences in streamer style, baseline audience composition, and store positioning.

Our panel structure defines each minute within a unique livestream session as a single observation, where index i denotes distinct livestream sessions and t indexes sequential minutes, allowing us to track real-time intra-stream shifts in viewer psychology and transaction metrics. Several model specifications adopt a unified empirical framework, differing only in their dependent variables. Specifically, the transformed outcome variable $\ln(Y_{i,t}^*)$ captures four separate dependent constructs, and our baseline regression specification is presented as Equation (1):

$$\ln(Y_{i,t}^*) = \alpha + \beta_1 Em_{i,t-1} + \beta_2 Cog_{i,t-1} + \beta_3 Sale_{i,t-1} + \beta_4 Follower_{i,t-1} + \beta_5 A_{i,t-1} + \gamma X_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

We adopt differentiated logarithmic transformations for distinct variable types when constructing $\ln(Y_{i,t}^*)$ and all lagged regressors. For lexical proportion indicators $Em_{i,t}$ (emotion expression) and $Cog_{i,t}$ (cognitive expression) that frequently take near-zero values, we apply $\ln(Em_{i,t+0.001})$ and $\ln(Cog_{i,t+0.001})$ to avoid undefined logarithmic calculations while minimally distorting the original distribution. For count-type indicators including

assistant intervention $A_{i,t}$, sales volume $Sales_{i,t}$ and new followers $Follower_{i,t}$ with discrete zero minute observations, we follow standard panel research practice and use $\ln(1 + A_{i,t})$, $\ln(1 + Sales_{i,t})$ and $\ln(1 + Follower_{i,t})$. The subscript $t - 1$ marks all predictors lagged by one minute to capture sequential temporal linkages between prior-minute audience states and current-minute outcomes.

The vector $X_{i,t}$ includes a full set of time-varying minute-level control variables including product characteristics, streamer characteristics, and social-context factors, such as product price, product category, discount, streamer gender, livestream duration, consumer interaction volume, fan group size, and real-time viewership.

We incorporate two layers of fixed effects to absorb unobserved confounding heterogeneity. The term μ_i stands for livestream session fixed effects, capturing time-invariant persistent disparities including streamer characteristics, stable baseline audience composition and long-term store positioning. In addition, our model incorporates multiple time dummy variables in λ_t for Chinese national holidays and days of the week fixed effects to control for seasonality and time trends. Finally, $\varepsilon_{i,t}$ is the idiosyncratic error term, which is allowed to correlate across consecutive minutes within the same livestream session i , while we impose independence across distinct livestream sessions. Given the high-frequency sequential nature of minute data, residual serial correlation across consecutive time points within one session is common; we cluster all regression standard errors at the livestream session level to allow arbitrary within-session residual correlation while maintaining independence across different broadcasts. The average variance inflation factor across all model specifications remains below 3.5, which demonstrates that multicollinearity does not pose a meaningful threat to our coefficient estimates.

Because minute-level observations are nested within livestream sessions, the analysis is well suited to examining real-time temporal associations within the observed livestream contexts. At the same time, these sessions are associated with two livestream rooms and multiple brands within the daily necessities category, so the model primarily captures within-context temporal variation. This structure therefore guides the interpretation of the estimates as temporal associations within the sampled livestream contexts.

5. Key Empirical Findings

5.1. Regression Results

To control for unobserved individual or time-specific differences and thereby estimate conditional associations between the independent variables and dependent variables, this study employs a panel data fixed-effects regression model. To reduce concerns about reverse causality, we created a time lag between the independent variables and dependent variables. Although this design cannot fully eliminate simultaneity or omitted-variable bias, it helps provide a more cautious temporal ordering of the observed associations. To reduce the influence of heteroscedasticity and outliers, we used the log transformation of values. The results are presented in Table 2.

As shown in Table 2, Column 1 (Model 1) presents the emotional contagion model. Results indicate that prior user emotion expression is significantly and positively associated with subsequent user emotion expression ($\beta = 0.177, p < 0.001$), supporting Hypothesis H1a. This hypothesis posits that in e-commerce live streaming scenarios, higher initial levels of user emotional expression correspond to greater positive emotional amplification among audiences over time. Column 2 (Model 2) outlines the cognitive amplification model. The findings demonstrate that prior user cognitive expression is significantly and positively associated with subsequent user cognitive expression ($\beta = 0.068, p < 0.001$), supporting Hypothesis H1b, which states that baseline user cognitive expression in e-commerce live streaming is positively related to subsequent cognitive responses among participating users.

Table 2. Regression Results: Cognitive and Emotional Mechanisms.

VARIABLES	Model 1 Lnemotion	Model 2 Lncognitive	Model 3 Lnemotion	Model 4 Lncognitive
L.Nemotion	0.177 *** (0.013)	0.190 *** (0.012)	0.167 *** (0.013)	0.168 *** (0.013)
L.Lncognitive	0.050 *** (0.005)	0.068 *** (0.005)	0.045 *** (0.005)	0.057 *** (0.006)
L.Insales	0.028 (0.023)	0.012 (0.034)	0.029 (0.023)	0.015 (0.031)
L.Infollows	0.017 (0.022)	−0.008 (0.024)	0.024 (0.022)	0.005 (0.022)
L.lninter_c	0.016 (0.042)	0.016 (0.039)	0.050 (0.039)	0.071 * (0.038)
L.lninter_a	−0.029 (0.029)	0.156 *** (0.008)	−0.035 (0.031)	0.132 *** (0.013)
L.lnfans	0.116 ** (0.046)	−0.048 (0.035)	0.098 ** (0.049)	−0.063 ** (0.031)
L.lnviews	−0.063 *** (0.023)	0.065 * (0.037)	−0.020 (0.030)	0.124 *** (0.040)
lnprice	0.059 *** (0.020)	0.064 (0.039)	0.047 *** (0.017)	0.041 (0.038)
product_category	0.041 (0.042)	0.107 * (0.059)	0.019 (0.038)	0.070 (0.054)
discount	0.089 *** (0.018)	−0.066 * (0.035)	0.081 *** (0.017)	−0.059 ** (0.025)
gender	0.046 (0.029)	0.008 (0.032)	0.054 (0.037)	0.019 (0.034)
duration	−0.139 *** (0.018)	−0.077 *** (0.014)	−0.160 *** (0.016)	−0.111 *** (0.012)
IA			0.136 *** (0.006)	
IC				0.304 *** (0.011)
Constant	−2.224 *** (0.161)	−2.248 *** (0.205)	−2.221 *** (0.163)	−2.188 *** (0.229)
Observations	4671	4671	4671	4671

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

To examine the moderating role of assistant intervention behavior, we incorporated two interaction terms into the model: IA (calculated as the product of lagged user emotion expression [L.Nemotion] and lagged assistant interaction [L.lninter_a]) and IC (calculated as the product of lagged user cognitive expression [L.Lncognitive] and lagged assistant interaction [L.lninter_a]). The regression coefficient for the interaction term IA was significantly positive ($\beta = 0.136$, $p < 0.001$), indicating that assistant intervention positively moderates the association between early-stage and later-stage emotion expression, supporting Hypothesis H2a. Similarly, the regression coefficient for the interaction term IC was also significant and positive ($\beta = 0.304$, $p < 0.001$), indicating that assistant intervention positively moderates the association between early-stage and later-stage cognitive expression, which supports Hypothesis H2b.

Furthermore, this study identifies an additional dynamic within e-commerce live streaming environments: consumer emotion expression and cognitive expression not only demonstrate self-reinforcing patterns but are also reciprocally associated with one another. Specifically, initial user emotion expression is significantly and positively associated with subsequent cognitive expression ($\beta = 0.190$, $p < 0.001$). Correspondingly, initial user cognitive expression is significantly and positively associated with subsequent emotion expression ($\beta = 0.050$, $p < 0.001$). Our findings reveal an asymmetric cross-association between user emotion and cognition during live streaming interactions: the association between emotion and subsequent cognition is stronger than the association between cog-

nitition and subsequent emotion. This asymmetry suggests that emotional signals may be more immediate correlates of real-time interaction dynamics, whereas cognitive processing unfolds more slowly and deliberately.

After examining the cognitive reinforcement and emotional contagion patterns in consumer interactions, we further examined how these two patterns are associated with e-commerce livestream performance. We selected follow behavior and purchasing behavior as key performance metrics, which were incorporated as dependent variables into a fixed-effects model. As shown in Table 3, the regression results show that early-stage user emotion expression is significantly and positively associated with purchasing behavior ($\beta = 0.026$, $p < 0.05$), supporting H3a. Early-stage user cognitive expression is significantly and positively associated with follow behavior toward the streamer ($\beta = 0.021$, $p < 0.05$), supporting H3b. In addition, the associations between early-stage emotion expression and follow behavior and the associations between early-stage cognitive expression and purchasing behavior were not statistically significant. The differential associations of cognitive reinforcement and emotional contagion with following and purchasing behavior are illustrated in Figure 2. Notably, assistant intervention is statistically and negatively associated with livestream sales ($\beta = -0.068$, $p < 0.05$). This finding indicates that assistant intervention corresponds to reduced sales performance in e-commerce live streaming.

Table 3. Regression Results: Sales and Follow Behavior.

VARIABLES	Model 5 Ln _{sales}	Model 6 Ln _{follow}
L.lnemotion	0.026 ** (0.012)	0.013 (0.008)
L.lncognitive	0.013 (0.009)	0.021 ** (0.010)
L.lnsales	0.211 *** (0.026)	0.069 *** (0.016)
L.lnfollows	0.053 *** (0.018)	0.148 *** (0.035)
L.lninter_a	−0.068 *** (0.026)	−0.009 (0.028)
L.lninter_c	0.001 (0.028)	0.001 (0.014)
L.lnfans	0.046 ** (0.021)	0.067 *** (0.019)
L.lnviews	0.209 *** (0.035)	0.335 *** (0.035)
lnprice	0.111 *** (0.033)	−0.009 (0.014)
product_category	0.142 *** (0.049)	−0.043 ** (0.020)
discount	−0.038 (0.032)	−0.015 (0.042)
gender	0.023 (0.038)	−0.003 (0.047)
duration	−0.015 (0.015)	−0.008 (0.011)
Constant	−0.696 *** (0.254)	−0.975 *** (0.179)
Observations	4671	4671

Note: *** $p < 0.01$; ** $p < 0.05$.

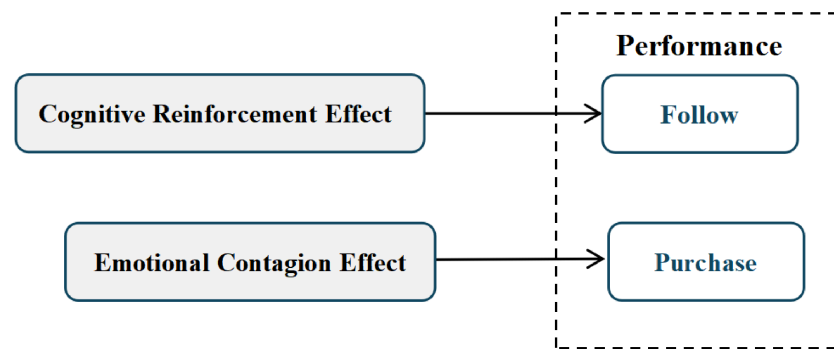


Figure 2. Dual Pathways of Cognitive Reinforcement and Emotional Contagion on Live Streaming Performance.

5.2. Robustness Test

To assess the robustness of the research results, we employ two robustness checks for our main analysis. All robustness tests are shown in Appendix A. First, we reconstruct the time window. We aggregate the original 1 min interval data into 5 min intervals and re-estimate the baseline model. Second, we exclude extreme observations. Given the significant heterogeneity across livestream sessions, we winsorize all continuous variables at the 1st and 99th percentiles to avoid biased estimates caused by outliers. The robustness test results show that the main findings remain consistent with the original results. These results suggest that the observed associations are not driven solely by the selected time window or extreme observations.

As an additional robustness check, we re-estimated the main models using random-effects panel regressions. The results, reported in Table A3, Panel C of Appendix A, are broadly consistent with the fixed-effects estimates. The temporal associations of user emotion expression and cognitive expression remain positive and significant, and the moderating effects of assistant intervention frequency on both pathways remain significant. The performance models also show the same pattern: emotion expression is positively associated with sales, cognitive expression is positively associated with follow behavior, and assistant intervention frequency is negatively associated with sales. These results further support the robustness of the main findings.

6. Discussion

6.1. Conclusions

This study investigates intertemporal emotional contagion, cognitive reinforcement, and the dual role of assistant intervention frequency in e-commerce live streaming. The key conclusions are summarized as follows.

6.2. Theoretical Contributions

This study makes three key theoretical contributions to the literature on e-commerce live streaming and consumer behavior.

First, this study extends the application of the CAB framework within the dynamic, real-time context of e-commerce live streaming. Prior CAB research has often examined cognition, affect, and behavior through relatively static or sequential relationships [6,60], whereas live streaming involves continuous, evolving user interactions. Building on the core logic of the CAB framework, this study shows that user cognitive expression and emotion expression exhibit temporal continuity and mutual association (the two dimensions are associated with each other bidirectionally). This finding enriches the contextual application of the CAB framework and provides empirical evidence for applying cognitive-affective models to real-time digital consumption settings. This contribution should therefore be

understood as a contextual application of established CAB and ELM-based dual-process perspectives rather than as the proposal of a new dual-pathway theory.

Second, this study further distinguishes the behavioral outcomes in the CAB framework by separating purchase behavior from follow behavior in e-commerce livestreaming. The classic CAB model often treats “behavior” as a broad outcome category, failing to distinguish between different types of user behaviors in specific consumption contexts and their corresponding cognitive–emotional associated mechanisms. In contrast, livestreaming contains both short-term transactional behavior and longer-term relational behavior. By examining purchase and follow behavior separately, this study shows that emotional expressions are more closely associated with purchase behavior in the observed livestream context. This finding is consistent with the core viewpoint of emotional contagion theory [23] that emotional arousal is closely related to impulsive and immediate behavioral responses, whereas cognitive expressions are more closely associated with follow behavior, which aligns with the theoretical logic of cognitive trust theory that sustained relational engagement relies on stable cognitive evaluation and trust. This distinction provides a more fine-grained application of the CAB framework to livestream consumer behavior.

Third, this study incorporates livestream assistants as a contextual moderator of livestream interaction dynamics. Existing research has mainly focused on streamer–user, user–user, or technology-driven interaction, while paying less attention to how human assistants shape real-time interaction processes [38,43,46]. By examining assistant intervention frequency, this study finds that assistant participation is negatively related to sales performance. One possible explanation is that assistant comments may redirect consumers’ attention from emotional contagion to more deliberate information processing. Because user emotion expression is more closely associated with immediate purchase behavior [55], assistant interventions that clarify product information or guide discussion may reduce uncertainty but also weaken emotion-driven purchase tendencies [27].

This interpretation is consistent with our finding that assistant intervention frequency is positively associated with the temporal continuity of user cognitive expression. Assistant participation may help organize product-related discussion and encourage later users to share more cognition-related content. Together, these findings suggest that human assistants may play a boundary role in livestream interaction management by strengthening cognitive interaction while potentially weakening the affective momentum behind immediate purchase behavior.

6.3. Management Insights

The findings of our study also have implications for practice. First, merchants may consider differentiated real-time interaction strategies based on the dual pathways of emotional contagion and cognitive reinforcement. Our empirical results suggest that emotional contagion is positively associated with immediate purchase conversion, whereas cognitive reinforcement is more closely associated with concurrent follower behavior. Accordingly, platforms and merchants can consider targeted, session-level interventions to support these two pathways. Strengthening the emotional atmosphere and interactive resonance may be associated with better product sales performance, while providing clear, professional product information may be associated with concurrent follower growth during live sessions.

Second, merchants should recognize the dynamic association between user emotion expression and cognitive expression in live streaming. Users’ emotional and cognitive expressions not only exhibit self-reinforcing patterns over time but also show asymmetric cross-associations: early emotion expression is more strongly associated with subsequent cognitive expression, while early cognitive expression is also associated with later emotion

expression. Operators may design integrated content that simultaneously nurtures positive emotion and clear cognition, rather than treating them as separate mechanisms. By aligning emotional stimulation and cognitive guidance in real time, merchants may observe stronger associations between the two pathways and improved overall live streaming engagement and performance.

Third, merchants should recognize the strategic value of live streaming assistants and clarify their three core operational functions: information supplementation, interactive facilitation, and emotional regulation. Consistent with our empirical evidence, assistant intervention frequency positively moderates the associations within emotional contagion and cognitive reinforcement patterns, yet assistant intervention is negatively associated with sales. Therefore, assistants should maintain an appropriate intervention intensity: providing timely information to reduce user uncertainty, responding to user comments to sustain interaction momentum, and regulating the interactive atmosphere to sustain positive user emotion without disrupting the natural process of emotional accumulation during live streaming.

6.4. Limitations of the Study

This study is not without unavoidable limitations, which also point to promising directions for future research. First, the comprehensiveness of streamer behavior data collection was constrained. A core analytical dimension of this research focuses on interactive mechanisms within the live streaming context; however, due to the unavailability of replay functions for some live streams, we were unable to collect streamer video materials and complete behavioral data. This data gap precluded the analysis of critical variables, such as nonverbal cues (e.g., body language, facial expressions, vocal tone), explanatory logic and pacing, and interactive response strategies, which are central to deciphering the cognitive and emotional transmission chain between streamers and users. The absence of this data dimension hinders a holistic explanation of the mechanisms underlying the cross-period cognitive–emotional reinforcement pattern, making it challenging to precisely disentangle the relative associations of streamer behavior and user interaction with performance outcomes.

Second, this study has limitations in measurement and empirical identification. LIWC emotional tone and cognitive-process words are used as proxies for user emotion expression and cognitive expression in bullet comments, but they cannot fully capture users' underlying psychological states. Although the human-coding validation provides convergent-validity evidence, these indicators should still be interpreted as linguistic proxies. In addition, assistant intervention is measured by comment frequency and therefore cannot distinguish assistant content, tone, or functional roles. Finally, although lagged variables, fixed-effects models, and control variables improve robustness, the observational design does not support strong causal claims. The findings should therefore be interpreted as associations rather than causal effects. Future research can use richer multimodal measures and stronger causal identification strategies to further examine these relationships.

Third, the empirical setting restricts generalizability. The data were collected from two livestream rooms on Taobao Live and focused on daily necessities. This design provides a useful real-time panel setting but offers limited cross-sectional variation across rooms, streamers, platforms, brands, and product categories. User decision logic, emotional cues, assistant roles, and platform mechanisms may differ substantially across industries and platforms. Therefore, the findings cannot be fully generalized to other livestream ecosystems without further testing. Future studies should expand the number of livestream rooms, include more product categories and platforms, and examine whether the observed associations remain stable across different market and cultural contexts.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Panel A: 5-Minute Time Window.

VARIABLES	(1) Lnsales	(2) Lnfollow	(3) Lnemotion	(4) Lncognitive	(5) Lnemotion	(6) Lncognitive
L.Lnemotion	0.042 ** (0.019)	0.016 (0.017)	0.070 *** (0.026)	0.090 *** (0.013)	0.056 ** (0.023)	0.079 *** (0.016)
L.Lncognitive	−0.090 * (0.049)	−0.011 (0.020)	0.065 ** (0.024)	0.137 *** (0.032)	0.060 * (0.035)	0.120 *** (0.036)
L.Lnsales	0.063 (0.050)	0.085 *** (0.011)	−0.021 (0.048)	−0.053 (0.053)	0.028 (0.048)	−0.007 (0.051)
L.Lnfollow	0.070 * (0.040)	0.144 *** (0.048)	0.011 (0.061)	0.111 ** (0.047)	0.016 (0.065)	0.099 ** (0.042)
L.Lninter_a	−0.045 ** (0.013)	0.004 (0.068)	0.098 (0.093)	0.154 * (0.093)	0.365 *** (0.110)	0.329 *** (0.088)
L.Lninter_c	0.013 (0.049)	−0.002 (0.015)	0.130 *** (0.023)	0.228 *** (0.023)	0.112 *** (0.034)	0.198 *** (0.030)
L.Lnfan	0.109 * (0.057)	0.154 *** (0.055)	0.054 (0.109)	0.047 (0.049)	0.038 (0.080)	0.026 (0.047)
L.Lnview	0.169 *** (0.057)	0.284 *** (0.054)	−0.080 ** (0.038)	−0.075 ** (0.030)	0.042 (0.038)	0.017 (0.035)
lnprice	0.074 *** (0.017)	0.019 (0.013)	0.056 * (0.032)	0.023 * (0.014)	0.044 (0.031)	0.014 (0.013)
product_category	0.196 *** (0.029)	0.027 (0.020)	0.004 (0.051)	0.013 (0.021)	−0.020 (0.043)	−0.006 (0.023)
discount	0.068 (0.057)	0.041 (0.070)	0.088 *** (0.033)	0.045 (0.047)	0.035 (0.031)	0.009 (0.032)
gender	0.088 (0.070)	0.043 (0.058)	0.071 ** (0.035)	0.030 (0.038)	0.074 (0.058)	0.031 (0.040)
duration	−0.001 * (0.000)	−0.000 (0.000)	−0.001 *** (0.000)	0.001 ** (0.000)	−0.003 *** (0.000)	−0.001 (0.000)
IA					0.353 *** (0.025)	
IC						0.373 *** (0.023)
Constant	−0.523 * (0.277)	−0.969 *** (0.162)	−3.005 *** (0.219)	−2.430 *** (0.145)	−3.310 *** (0.243)	−2.584 *** (0.224)
Observations	933	933	933	933	933	933

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2. Panel B: Winsorized Sample (1%).

VARIABLES	(1) Lnsales	(2) Lnfollow	(3) Lnemotion	(4) Lncognitive	(5) Lnemotion	(6) Lncognitive
L.lnemotion	0.024 ** (0.012)	0.012 (0.008)	0.187 *** (0.016)	0.195 *** (0.013)	0.177 *** (0.016)	0.174 *** (0.014)
L.lncognitive	0.013 (0.008)	0.020 ** (0.010)	0.049 *** (0.006)	0.066 *** (0.005)	0.043 *** (0.005)	0.055 *** (0.006)
L.lnsales	0.204 *** (0.025)	0.069 *** (0.016)	0.033 (0.023)	0.018 (0.034)	0.033 (0.022)	0.019 (0.031)
L.lnfollow	0.054 *** (0.018)	0.139 *** (0.035)	0.023 (0.023)	−0.002 (0.023)	0.032 (0.022)	0.014 (0.020)
L.lninter_a	−0.069 *** (0.026)	−0.006 (0.030)	0.027 (0.045)	0.022 (0.040)	0.058 (0.043)	0.073 * (0.041)
L.lninter_c	0.003 (0.027)	0.004 (0.016)	0.009 (0.023)	0.177 *** (0.009)	0.005 (0.025)	0.155 *** (0.015)
L.lnfan	0.044 * (0.025)	0.065 *** (0.018)	0.143 *** (0.045)	−0.031 (0.036)	0.130 *** (0.049)	−0.039 (0.032)
L.lnview	0.213 *** (0.037)	0.335 *** (0.036)	−0.113 *** (0.023)	0.024 (0.038)	−0.067 ** (0.031)	0.089 ** (0.041)
lnprice	0.110 *** (0.033)	−0.008 (0.015)	0.069 *** (0.021)	0.071 * (0.042)	0.057 *** (0.018)	0.047 (0.040)
product_category	0.142 *** (0.048)	−0.043 ** (0.020)	0.042 (0.046)	0.110 * (0.066)	0.021 (0.042)	0.074 (0.061)
discount	−0.044 (0.033)	−0.015 (0.043)	0.104 *** (0.020)	−0.046 (0.035)	0.093 *** (0.022)	−0.046 (0.028)
gender	0.026 (0.040)	−0.002 (0.045)	0.060 ** (0.027)	0.024 (0.034)	0.070 * (0.036)	0.037 (0.037)
duration	−0.000 ** (0.000)	0.000 (0.000)	−0.000 *** (0.000)	−0.000 *** (0.000)	−0.001 *** (0.000)	−0.000 *** (0.000)
IA					0.138 *** (0.006)	
IC						0.309 *** (0.012)
Constant	−0.770 *** (0.253)	−1.030 *** (0.188)	−2.630 *** (0.134)	−2.423 *** (0.248)	−2.710 *** (0.159)	−2.502 *** (0.271)
Observations	4671	4671	4671	4671	4671	4671

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.**Table A3.** Panel C: Random-Effects Model.

VARIABLES	(1) Lnemotion	(2) Lncognitive	(3) Lnemotion	(4) Lncognitive	(5) Lnsales	(6) Lnfollow
L.lnemotion	0.186 *** (0.016)	0.195 *** (0.013)	0.177 *** (0.016)	0.174 *** (0.014)	0.026 ** (0.013)	0.014 * (0.008)
L.lncognitive	0.048 *** (0.005)	0.067 *** (0.005)	0.043 *** (0.005)	0.056 *** (0.006)	0.013 (0.009)	0.020 ** (0.010)
L.lnsales	0.031 (0.022)	0.014 (0.034)	0.032 (0.022)	0.016 (0.031)	0.211 *** (0.027)	0.069 *** (0.016)
L.lnfollow	0.023 (0.023)	−0.004 (0.023)	0.032 (0.021)	0.011 (0.020)	0.055 *** (0.018)	0.148 *** (0.036)
L.lninter_a	0.031 (0.044)	0.024 (0.040)	0.061 (0.042)	0.073 * (0.040)	−0.072 *** (0.026)	−0.005 (0.030)
L.lninter_c	0.012 (0.022)	0.179 *** (0.009)	0.008 (0.024)	0.156 *** (0.014)	0.001 (0.027)	0.006 (0.015)

Table A3. Cont.

VARIABLES	(1) Lnemotion	(2) Lncognitive	(3) Lnemotion	(4) Lncognitive	(5) Lnsales	(6) Lnfollow
L.Infan	0.139 *** (0.046)	−0.035 (0.035)	0.125 ** (0.050)	−0.044 (0.030)	0.049 ** (0.022)	0.069 *** (0.019)
L.Inview	−0.119 *** (0.023)	0.035 (0.037)	−0.075 ** (0.029)	0.095 ** (0.040)	0.210 *** (0.035)	0.327 *** (0.034)
Inprice	0.069 *** (0.021)	0.069 * (0.041)	0.057 *** (0.018)	0.046 (0.039)	0.111 *** (0.032)	−0.007 (0.015)
category	0.043 (0.046)	0.108 * (0.065)	0.022 (0.042)	0.073 (0.060)	0.143 *** (0.048)	−0.043 ** (0.020)
discount	0.109 *** (0.021)	−0.055 (0.036)	0.099 *** (0.022)	−0.052 * (0.028)	−0.040 (0.032)	−0.012 (0.043)
gender	0.065 ** (0.028)	0.018 (0.033)	0.076 ** (0.037)	0.034 (0.038)	0.025 (0.039)	−0.002 (0.046)
duration	−0.000 *** (0.000)	−0.000 *** (0.000)	−0.001 *** (0.000)	−0.000 *** (0.000)	−0.000 ** (0.000)	0.000 (0.000)
IA			0.134 *** (0.005)			
IC				0.303 *** (0.011)		
Constant	−2.615 *** (0.130)	−2.466 *** (0.243)	−2.685 *** (0.153)	−2.525 *** (0.268)	−0.753 *** (0.248)	−0.988 *** (0.178)
Observations	4671	4671	4671	4671	4671	4671

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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