

The Impact of Live Comment Characteristics on Subsequent Live Streaming Sales and User Retention

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ABSTRACT

Live comment, as a primary mean of live interaction, addresses the issue of information asymmetry that viewers face during commercial live streaming. While live comments generally enhance user engagement, the varying processing strategies viewers employ towards the same information can lead to different impacts of live comment content on their decision-making. However, existing research has yet to examine the specific mechanisms through which these differentiated processing strategies affect viewer decisions. This gap limits our deep understanding of how live interactions affect viewer behavior in social media commercial live streaming. This paper used the ELM model to investigate how different information processing strategies on live comments dynamically influence product sales and user retention. By scraping data from 61 TikTok (China) live streaming events, we collected 9,636,136 comments, segmented into 3,854 time slices. Our empirical study finds that the quantity of live comments exhibits an inverted U-shaped relationship with immediate sales and user retention. Real-time purchase information and free chat-related comments positively impact immediate sales and user retention, while comments required for participation in lucky draws have the opposite effect. Interestingly, positive product-related comments negatively impact real-time user retention, while negative product-related comments are positively associated with real-time sales. Our research contributes to extend consumer behavior models by capturing the distinct dynamic state of live streaming and provide insights for business to optimize their live streaming performance.

Keywords: Live streaming, live comment, ELM, user retention, sales, dynamic effect.

INTRODUCTION

Live streaming e-commerce has become the fastest growing new form of e-commerce in China. According to the 53rd Statistical Report on China's Internet Development, as of December 2023, the user size of live streaming in China had reached 816 million, and 73.2% of online consumers have bought live streaming merchandise. Data from iResearch showed that the scale of China's live streaming e-commerce market reached 4.9 trillion RMB in 2023, with a year-on-year growth rate of 35.2%. Whether from the perspective of consumers or e-tailers, live streaming will become the mainstream e-commerce mode in China. Live streaming e-commerce has emerged as an extension of TV shopping in the digital age. However, live streaming e-commerce not only incorporates the features of television shopping (visual product demonstration by streamers) but also includes the consumer's exploration of product information typical of traditional e-commerce and the live interactive elements of offline shopping (Yun et al., 2023; Han, 2022). Overall, live streaming e-commerce can be seen as a combination of television shopping, traditional e-commerce shopping, and live interaction. It delivers more signals, such as verbal and non-verbal expressions from the streamer and live comments from viewers. Additionally, the mechanisms through which consumers process these signals are more complex. Gaining a deeper understanding of these mechanisms is essential for enriching theoretical and practical insights into consumer behavior within live streaming e-commerce domain.

Existing research has extensively studied the product demonstration by streamers in television shopping side and consumer exploration in traditional e-commerce side. In terms of product demonstration by streamers, existing research has focused on various streamer-centric aspects such as streamer narrative presentation, emotion expression, linguistic styles, background design, and coping strategies. For consumer exploration for products in live streaming shopping, current studies have examined multiple facets including perceptual consistency, consumer values, consumer appeal and consumer attributes. In the context of live interaction within live streaming e-commerce, research on live comments remains notably limited, even though live comments serve as a primary approach of interaction. The limited studies primarily focus on the interactive functionality (Ma et al., 2022), activeness (Diao et al., 2023) and overall emotional tendency (Zeng et al., 2022) of live comments. However, consumers do not merely engage in such a broad analysis of live comment information. There is still a lack of understanding on how different information processing willingness impact viewers' decision-making in social media live streaming e-commerce. Additionally, live comments are highly time-sensitive. Only recent comments are visible and processed in real-time, as comments from even a few minutes earlier are no longer accessible. Most existing studies on live comments adopt an event-level analysis approach, which fails to account for the real-time nature of live comments. This limitation impedes our understanding of how the real-time effects of live comments influence viewer decision-making in live-streaming e-commerce.

Existing live streaming e-commerce channels can be categorized into traditional e-commerce platform-based live streaming (e.g., Taobao, JD.com) and social media platform-based live streaming (e.g., TikTok, Weibo). The viewer's purposes differ when watching live streams on different platforms. Research on traditional e-commerce platforms primarily focus on consumer purchase behavior and purchase motivations due to viewers' emphasis on product transactions. In contrast, social media live streaming attracts some consumers for entertainment, shifting research attention to not only purchase intention but also continuous watching and virtual gifting. Additionally, social media live streaming is essentially a social platform augmented with live sales functionality, rather than a traditional profit-oriented e-commerce platform that mainly provides shopping functions. Existing research on social media live streaming consumer behavior examines both sales and non-consumption behaviors, such as continuous watching and loyalty or following. While emphasizing sales, our study focuses on real-time effects of live comment, emphasizing immediate feedback (user retention). By analyzing how different live comment information processing willingness affect dynamic sales and user retention, we aim to provide a comprehensive understanding of viewer interaction patterns in this context.

The Elaboration Likelihood Model (ELM) explains how individuals process persuasive information through two distinct routes: the central route and the peripheral route, which ultimately leads to changes in attitudes and subsequent behaviors. This paper employs ELM because live comments can essentially be viewed as persuasive information that influences viewers' real-time decision-making processes. Additionally, consumers adopt one of the information processing routes in different stages when engaging in social media live streaming e-commerce. When viewers are highly interested in a product or interactive content, they invest more cognitive effort in processing the content and emotions conveyed through live comments, engaging in the central route. Conversely, when they view the live content as entertainment, their decisions are influenced by intuitive cues, aligning with the peripheral route. Existing studies often examine the quantity, length, and real-time purchase information of live comments as peripheral cues (Fei et al., 2021; Diao et al., 2023). Unlike previous work, our model integrates these factors into the peripheral route to simulate a more realistic information processing scenario. Additionally, existing research indicates that the semantic richness and emotional features of live comments play a crucial role in consumers' information processing (Peng et al., 2016). Through practical observations, live comments can be broadly categorized into product-related, free chat-related, and lucky draw-related categories. In this study, we focus on product-related live comments for sentiment analysis, as they directly influence viewers' evaluations of the product and live content. Therefore, this paper considers product-related live comments under different emotional tendencies, free chat-related live comments and lucky draw-related live comments as central path. Using real platform data, we aim to model the impact of viewer information processing willingness on viewing and purchasing decisions in social media live streaming e-commerce.

One of the core assumptions of the ELM is that individuals' choice of information processing paths is influenced by a variety of factors, which scholars often consider as moderators. These moderators help explain why individuals may exhibit different responses in the same persuasive context, accounting for individual differences in information processing. Furthermore, Moderators enable ELM to better accommodate dynamic environments. In this study, we selected top streamers from hourly leaderboard as a moderator. The hourly leaderboard represents the dynamic external environment that viewers encounter when processing live comment information. Also, the rankings on leaderboard also reflect the combined influence of various external factors, such as popularity, appeal and cost-effectiveness. This allows us to assess the immediate and comprehensive impact of dynamic environmental changes on viewers' information processing strategies and helps to understand the varying effects of live comments in live events hosted by different tiers of streamers.

In this study, we examine our conceptual model using a large dataset collected from TikTok (China), which has the largest social media live streaming e-commerce business in China. We collected 9,636,136 live comments in TikTok (China) from February 22, 2024, to March 5, 2024, and performed an empirical analysis. After conducting our empirical analysis of live comment data, we obtained valuable insights and made several significant contributions. First, this study is one of the few to explore the real-time effect of live comments on viewer decision-making. Existing research predominantly analyzes by using event-level data, neglecting the real-time impact of live comments. Secondly, we thoroughly consider the differing processing routes of viewers based on their specific viewing purposes. By examining the match between variables, we aim to measure a more comprehensive and accurate consumer information processing flow. Finally, based on the ELM, this study provides an insightful framework for better understanding the live interaction mechanisms of viewers in social media live streaming e-commerce, offering a practical model for sellers.

LITERATURE REVIEW

Live Comment in Live Streaming E-commerce

The live comments on the live streaming interface serve as a primary channel to eliminate user information asymmetry, leading to extensive research conducted by numerous scholars in this field. Previous research on live comments in commercial live streaming has primarily focused on their theoretical functionality, degree of interaction, and overall sentiment tendencies. Early studies on live comments primarily employed survey or interview methods to investigate the overall functional effects of live comments on consumer decision-making. However, these subjective research methods may lead to inconsistencies or inaccuracies between participants' thoughts expressed in questionnaires and their behaviors exhibited while watching commercial live streaming.

Utilizing interaction and transaction data from live streaming platforms can more authentically reflect how viewers process live comment information while watching commercial live streaming. Currently, many scholars have integrated live comments into theoretical models that examine consumer decision-making. For example, Zheng et al. (2022) used live comment quantity as one of the indicators for consumer engagement, while Fei et al. (2021) analyzed both live comment quantity and length as social cues to explore their impact on consumer purchasing behavior. However, they tend to focus more on the intuitive features of live comments, neglecting the impact of interactive text content on consumer behavior. Some scholars have investigated the sentiment of live comments (Ma et al., 2024) and their specific categories (Xiao et al., 2023), but the event-level data or survey data they employed only broadly captures consumers' perceptions of live comment information, failing to account for the real-time effect of live comments. Although Zeng et al. (2022) utilized data from Taobao (Live) to examine the real-time impact of live comments on consumer purchasing decisions. Taobao, as a traditional e-commerce platform, often sees viewers discussing product content and promotional information in live comment interface. Unlike the more focused live comments found in traditional e-commerce platform, the live comments in social media commercial live streaming are significantly more diverse. Therefore, solely considering the emotional dimension neglects the richness of this diversity and the different potential outcomes it may lead to. Building on these research gaps, this study aims to integrate web crawling techniques with text mining to gain a minute-level dataset, which help us get to know the real-time and objective impact of live comment information on consumer decision when watching social media live streaming e-commerce. By considering various intuitive characteristics and examining the match between the sentiment and types of live comments, we seek to provide insights into how viewers process third-party information while watching social media commercial live streaming

ELM

The ELM is a psychological theory that addresses the process of persuasion. This theory is a 'dual-process' model, elucidating two distinct pathways by which persuasion operates: the central route and the peripheral route. In the central route, consumers exhibit heightened interest, motivation, and cognitive aptitude to engage with information, as 'elaboration likelihood' is said to be high. They conscientiously evaluate the merits of presented arguments and critically assess the attributes associated with them, resulting in potential shifts in attitudes, purchase intentions, and real-time purchasing behaviors. For the peripheral route, consumers lacking in interest, motivation and cognitive resources for extensive information processing may rely on peripheral cues to shape their attitudes, purchase intentions, and eventual purchasing decisions, which means low elaboration likelihood (Petty & Cacioppo, 1981). It is also important to note that the central and peripheral routes represent positions on a continuous dimension ranging from high to low likelihood of issue-relevant thinking rather than two mutually exclusive and exhaustive 'types' of information processing (Cacioppo et al., 1985). The process of persuasion exists in various domains of life. In recent years, the ELM has been extended to various domains such as advertising, organizational management, personalized recommendations, online review and privacy protection.

In the field of live streaming e-commerce, the ELM has also been widely applied. Compared to traditional e-commerce, consumers are simultaneously influenced by a greater variety of information sources when watching live streaming e-commerce. Therefore, existing studies that apply the ELM to analyze viewer behavior in live streaming e-commerce encompass multiple dimensions, such as the streamer, viewer, acquaintances, product, interactive functionality, live comments, and technological factors. In studies utilizing surveys as the research method, researchers often consider multiple dimensions simultaneously, which helps to comprehensively examine the effects of different factors on viewers' decision-making. For example, Chen et al. (2020) found that the central route (perceived product quality and brand awareness) and the peripheral route (value similarity with the streamer, streamer's reputation, and perceived product knowledge from the streamer) are both positively correlated with viewers' purchase decisions. However, the survey method is typically retrospective, and consumers' real-time reactions may not align with their self-reported behaviors after the event. As a primary method for addressing information asymmetry, many scholars have incorporated interactive functionality or live comments into their research within the framework of the ELM. In the detailed studies on live comments, Gao et al. (2021) employed survey methods, revealing that the comprehensiveness of live comment content positively influences consumers' purchase intention. Additionally, the semantic richness and sentiment tendency of live comments play a crucial role in influencing how viewers process information during live-streaming sessions (Peng et al., 2016). Xiao et al. (2023) sought to investigate the impact of live comments related to products and promotions on product sales. However, no research has yet comprehensively considered the match between comment types and sentiment tendency. The match would better reflect the thoughtful and deliberate nature of viewers' information processing on central route.

Drawing on previous studies of live comment, we identified three key intuitive cues that scholars most frequently examine: live comment quantity, length, and herd messages (real-time purchase information) into the peripheral route. In social media live streaming e-commerce, interactions between consumers and between consumers and streamers extend beyond product content. Through objective observation, we found that in addition to product-related comments, there are also a significant number of free chat-related and lucky draw-related live comments. Since free chat-related and lucky draw-related comments are unrelated to product content and do not directly influence viewers' perception of product attributes, we conducted sentiment analysis solely on product-related comments. Therefore, our central route is categorized into positive, negative, and neutral product-related comments, free chat-related comments and lucky draw-related comments.

HYPOTHESIS DEVELOPMENT

Peripheral Route

When viewers are interested in a product, more live comments provide them with more third-party viewpoints. Conversely, less interest leads to lower information processing willingness. A constant flow of live comments can create an engaging atmosphere, heightening viewer excitement and sustaining their interest in watching. However, an excessive number of comments may lead to information overload. Therefore, we propose the hypotheses:

H1a: The quantity of live comments has a positive effect on subsequent sales. (**H1b** ~ retention)

Longer live comments can facilitate in-depth discussions and interactions among viewers, enhancing the interactivity of live streaming and enriching live content, thus enhancing viewer watching intention. Also, longer live comments contain more information about product features, usage methods and other consumers' purchase experiences. This provides strong support for viewers to make purchase decisions. Therefore, we propose the hypotheses:

H2a: The length of live comments has a positive effect on subsequent sales. (**H2b** ~ retention)

Real-time purchase information provides viewers with positive cues about the product, and the streamer's use of scarcity marketing may trigger impulsive purchases. Additionally, seeing more people buy a particular product acts as a social stimulus, drawing viewers' attention (Granovetter & Soong, 1986) and sustaining their interest in the live streaming event.

H3a: The real-time purchase information has a positive effect on real-time sales. (**H3b** ~ retention)

Central Route

Positive product-related comments help viewers better understand the product's advantages and encouraging purchase decisions. Furthermore, such endorsements indirectly reflect the streamer's ability to select quality products, increasing viewers' anticipation for future product introductions and encouraging continued engagement with the live streaming event.

H4a: Positive product-related live comments have a positive effect on real-time sales. (**H4b** ~ retention)

Negative product-related comments can diminish viewers' trust in both the streamer and the product. Sometimes, these comments are perceived as criticisms of the streamer or the content, reducing viewers' willingness to continue watching. Additionally, viewers may be influenced by mentions of product flaws or negative experiences in the comments, leading to skepticism about the product and negatively impacting their real-time purchase intentions.

H5a: Negative product-related live comments have a negative effect on real-time sales. (**H5b** ~ retention)

Neutral product-related comments provide additional information and perspectives, enriching the live streaming content and enhancing viewer engagement and interaction. This further strengthens viewers' emotional connection and involvement, encouraging them to continue watching. Additionally, neutral product-related comments help viewers gain a more comprehensive understanding of product features and user experiences, boosting their confidence in the product and increasing their purchase intentions. Therefore, we propose the hypotheses:

H6a: Neutral product-related live comments have a positive effect on real-time sales. (**H6b** ~ retention)

User-generated free chat-related comments (non-product content) provide additional entertainment during live events, ensuring that viewers remain entertained without feeling that the content is monotonous. Additionally, free chat between viewers can involve discussions of industry trends, market insights, and related information, which can help other consumers gain a more well-rounded understanding of the product's value proposition and make more informed decisions. We propose the hypotheses:

H7a: Free chat-related live comments have a positive effect on real-time sales. (**H7b** ~ retention)

The evolution of live streaming lucky draws has gone beyond simple click-to-participate actions. Viewers are now required to send pre-set messages in the live comment interface as a condition for participation. These messages often include the live streaming theme, promotional details, or upcoming announcements, serving as reminders for the viewers. However, within a short time, the live comment interface becomes flooded with repetitive content, posing a significant challenge for viewers trying to gather relevant information. After these comments initially appear, the continuous scrolling of identical messages becomes meaningless and may even have a counterproductive effect. Therefore, we propose the hypotheses:

H8a: Lucky draw-related live comments have a negative effect on real-time sales. (**H8b** ~ retention)

Moderating Effect

This paper uses top streamers on the hourly leaderboard as a moderator. For viewers with weaker information processing abilities, the visual features of the live comments are more attractive and they pay more attention to the speed of the live comments, creating a lively atmosphere for them. The top streamers generally have higher sales, resulting in a large amount of real-time purchase information appearing in the live comment interface, which easily triggers viewers' impulse buying behavior. For viewers with stronger information processing abilities, they tend to carefully process live comment information, gaining more entertainment and engagement from live comment interactions. Moreover, they pay more attention to the different perspectives of product comments from both the streamers and viewers, enhancing their trust in the products. Therefore, we propose the following hypothesis:

H9a: The top streamers on hourly leaderboard moderates the relationship between peripheral path and sales. (**H9b** ~ retention)

H10a: The top streamers on hourly leaderboard moderates the relationship between central path and sales. (**H10b** ~ retention)

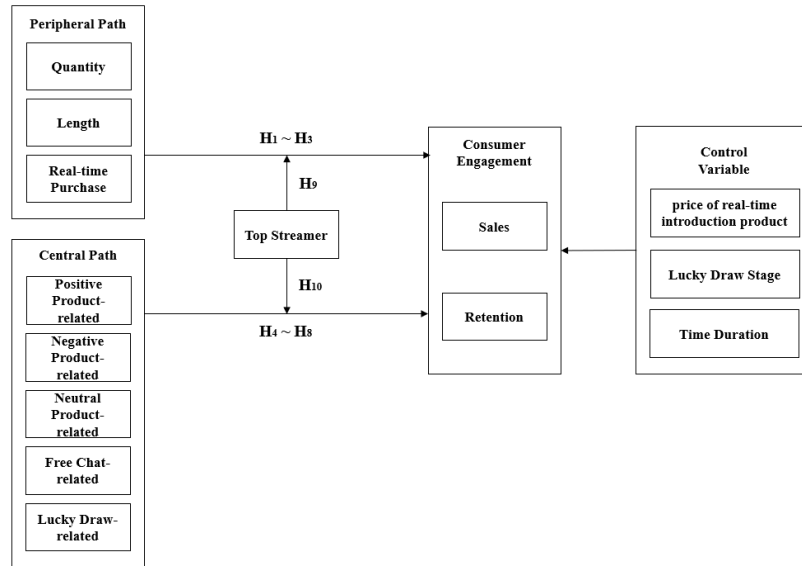


Figure 1: Research Model

DATASET, VARIABLES AND MODEL DEVELOPMENT

Data in this paper was crawled from live streaming events on TikTok (China) from February 22nd to March 5th, comprising a total of 103 events. After excluding events with insufficient total duration and low comment counts, 61 events with valid data remain. In total, the dataset consists of 9,636,136 live comments, aggregated into 3,854 time periods using 3-minute intervals.

Our study employs a dynamic analysis of consumer decision-making by using the average number of viewers within every three-minute period as the measure of user retention. we integrate data statistics from third-party platforms: Chanmama.com and match real-time sales data on a one minute-to-one minute basis to our dataset. We use the average sales volume over three-minute interval as the sales figure for concerned period. We assess the quantity and length of live comments, as well as real-time purchasing information by measuring the number of comments, total character count, and order volume within specific time periods. Based on all the live comment content obtained, we have constructed our own corpus to distinguish between product-related live comment and free chat-related live comment. For live comments on products, we utilize SnowNLP for sentiment analysis of the live comments. We count different types of live comments within specific time periods as indicators to measure each variable.

This study proposes to construct a hierarchical log-linear auto-regressive model. Multiple regression models.

$$\log(Sales_{t+1}) = \beta_0 + \beta_1 \log(Quantity_t) + \beta_2 \log(Quantity-sq_t) + \beta_3 \log(Length_t) + \beta_4 \log(RTPI_t) + \beta_5 \log(Positive_t) + \beta_6 \log(Negative_t) + \beta_7 \log(Neutral_t) + \beta_8 \log(Freechat_t) + \beta_9 \log(Luckydraw_t) + \alpha_1 \log(Price_t) + \alpha_2 \log(LDP_t) + \alpha_3 \log(Time_t) + e_i \quad (1)$$

$$\log(Retention_{t+1}) = \delta_0 + \delta_1 \log(Quantity_t) + \delta_2 \log(Quantity-sq_t) + \delta_3 \log(Length_t) + \delta_4 \log(RTPI_t) + \delta_5 \log(Positive_t) + \delta_6 \log(Negative_t) + \delta_7 \log(Neutral_t) + \delta_8 \log(Freechat_t) + \delta_9 \log(Luckydraw_t) + \varphi_1 \log(Price_t) + \varphi_2 \log(LDP_t) + \varphi_3 \log(Time_t) + e_i \quad (2)$$

EMPIRICAL RESULT

Descriptive Analysis and Main Effect

Although some correlation coefficients exceeded 0.6, all variable inflation factor (VIF) values were below 10 (largest VIF equals 4.40), suggesting no major multicollinearity issues. Except for H2a, H4a, H5a, H6a, H10a, and H4b, all other hypotheses were supported.

Table 1: The Pearson's Correlation

Variables	1	2	3	4	5	6	7	8	9	10
1. Quantity	1									
2. Length	.363***	1								
3. RTPI	.153***	-.012	1							
4. Positive	.285***	.004	.312***	1						
5. Negative	.179***	.001	.294***	.651***	1					
6. Neutral	.328***	-.118***	.267***	.681***	.617***	1				
7. FreeChat	.601***	.141***	.286***	.319***	.291***	.245***	1			
8. LuckyDraw	.555***	.324***	-.191***	-.331***	-.401***	-.198***	.011	1		

9. Sales	.192***	.029	.299***	.293***	.257***	.233***	.321***	-.102***	1	
10. Retention	.472***	.114***	.321***	.386***	.281***	.308***	.669***	.036*	.420***	1

Table 2: OLS Regression Result

	Sales				User Retention			
IV	Main	Moderate	Robust-2min	Robust-4min	Main	Moderate	Robust-2min	Robust-4min
Quantity	15.646*** (2.903)	25.018*** (4.919)	15.457*** (2.614)	24.288*** (5.163)	22.251*** (1.062)	19.316*** (1.561)	20.043*** (0.870)	36.847*** (2.093)
Quantity-sq	-7.669*** (1.444)	-12.363*** (2.452)	-7.569*** (1.299)	-12.016*** (2.573)	-10.841*** (0.528)	-9.302*** (0.778)	-9.725*** (0.432)	-18.139*** (1.043)
Length	0.008 (0.108)	0.107 (0.131)	-0.028 (0.096)	-0.040 (0.114)	0.115** (0.040)	0.031 (0.041)	0.134*** (0.032)	0.145** (0.046)
RTPI	0.236*** (0.016)	0.237*** (0.021)	0.263*** (0.014)	0.258*** (0.018)	0.103*** (0.006)	0.066*** (0.007)	0.083*** (0.005)	0.133*** (0.007)
Positive	0.052 (0.051)	0.053 (0.060)	0.060 (0.043)	0.121* (0.055)	-0.074*** (0.019)	-0.122*** (0.019)	-0.061*** (0.014)	-0.091*** (0.022)
Negative	0.217*** (0.043)	0.246*** (0.051)	0.193*** (0.037)	0.170*** (0.046)	-0.052*** (0.016)	-0.049*** (0.016)	-0.042*** (0.012)	-0.071*** (0.019)
Neutral	-0.095+ (0.051)	-0.136* (0.066)	-0.102* (0.044)	-0.076 (0.055)	0.071*** (0.019)	-0.036+ (0.021)	0.074*** (0.015)	-0.079*** (0.022)
Freechat	0.151*** (0.034)	0.024 (0.047)	0.131*** (0.030)	0.159*** (0.036)	0.379*** (0.012)	0.244*** (0.015)	0.375*** (0.010)	0.373*** (0.014)
Luckydraw	-0.067*** (0.014)	-0.052** (0.017)	-0.082*** (0.013)	-0.055*** (0.014)	-0.034*** (0.005)	-0.077*** (0.005)	-0.037*** (0.004)	-0.036*** (0.006)
Price	-0.070*** (0.020)	-0.119*** (0.021)	-0.067*** (0.018)	-0.084*** (0.021)	0.130*** (0.007)	0.076*** (0.007)	0.129*** (0.006)	0.126*** (0.008)
LDP	0.262 (0.193)	0.257 (0.190)	0.142 (0.140)	0.614** (0.230)	0.121 (0.071)	0.093 (0.060)	0.025 (0.047)	0.202* (0.093)
Time	0.020*** (0.006)	0.024*** (0.006)	0.015** (0.006)	0.013* (0.006)	0.033*** (0.002)	0.042*** (0.002)	0.033*** (0.002)	0.032*** (0.003)
TopRank		1.962* (0.897)				2.364*** (0.285)		
Quantity× TopRank		-20.575*** (6.157)				-6.268*** (1.953)		
Quantity-sq × TopRank		10.320*** (3.060)				2.861*** (0.971)		
Length× TopRank		-0.371 (0.250)				0.206** (0.079)		
RTPI× TopRank		-0.089** (0.033)				0.0003 (0.011)		
Positive× TopRank		-0.057 (0.114)				0.143*** (0.036)		
Negative× TopRank		-0.138 (0.091)				-0.041 (0.029)		
Neutral× TopRank		0.091 (0.112)				0.091** (0.035)		
Freechat× TopRank		0.069 (0.078)				0.123*** (0.025)		
Luckydraw × TopRank		-0.086** (0.030)				0.075*** (0.010)		
Constant	-0.385 (0.376)	0.092 (0.467)	-0.136 (0.339)	-0.189 (0.407)	1.821*** (0.138)	2.658*** (0.148)	1.953*** (0.113)	1.572*** (0.165)
Observation	3854	3854	5739	2910	3854	3854	5739	2910

Robust Test

To ensure the robustness of the core results, this study conducted a robustness check by adjusting the time interval measurements. When the interval was changed from three to two or four minutes, most regression results remained consistent with the main findings. However, with a four-minute interval, the positive effect of neutral comments on user retention became negative, and their negative effect on sales became non-significant. These findings confirm the robustness of the empirical results across different time intervals.

DISCUSSION AND IMPLICATIONS

Discussion

Interestingly, the results show that negative product-related live comments have a significant positive impact on sales, which is contrary to our hypothesis. On one hand, we believe this may be due to the fact that positive comments far outnumber negative ones, making the negative live comments more attention-grabbing and arouse people's curiosity. Particularly in the context of live streaming e-commerce, consumers are unable to fully understand the appearance, features, and other information about the product, making it easier to increase their desire for the item. On the other hand, a moderate number of negative reviews can also enhance the reliability of a product. We present the following reasons for the result of hypothesis 4b. We believe that an excess of positive reviews leads to a reduction in perceived credibility of both the product and the streamer, especially in the context of live streaming e-commerce. When the streamer predominantly endorses a product alongside a flood of positive comments, viewers may perceive these comments as manipulated rather than genuine user feedback. This perceived lack of authenticity reduces user trust in both the platform and the streamer.

Implications

First, by introducing the ELM into the field of live comments in live streaming e-commerce, it enriches the literature on live comments in e-commerce and reveals how different information processing willingness influence product sales and user retention. Moreover, this study innovatively matched ELM's central route factors, providing a more real representation of the deep information processing mechanisms. Second, the study explores the impact of dynamic information processing on consumer decision-making under various boundary conditions during commercial live streaming. Unlike previous research that examined boundary effects from a single dimension, this study introduces a comprehensive measure: top streamers on hourly leaderboard. This multifaceted perspective deepens the understanding of consumer decision-making mechanisms in complex environments. Finally, the study examines the real-time nature of live comments, offering a dynamic analysis of how consumer decisions are influenced by immediate contexts.

This study emphasizes that while live comments increase interaction and event visibility, they do not directly drive purchase decisions unless accompanied by promotions. Additionally, the research highlights the importance of optimizing interaction formats (such as lucky draws and free chats) to enhance viewer engagement and the overall success of live streaming events, providing valuable strategies for merchants and streamers.

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