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Original Paper

Research on the Impact of Real-Time Interaction on Consumer Purchasing Behavior in Livestream E-commerce

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Abstract

With the rapid development of the livestream e-commerce industry, research on consumer purchasing behavior based on live streaming platforms has become extensive. However, studies examining the relationship between real-time interaction and consumer purchasing behavior remain relatively limited. As real-time interaction is a key advantage of livestream e-commerce, this study investigates the mechanism influencing consumer purchasing behavior from the perspective of Streamer-viewer interaction. Grounded in social influence theory, it explores how different dimensions of real-time interaction affect consumer purchasing behavior in livestream contexts. By collecting 9,684 minutes of dynamically structured real-time data, over 2.95 million words of Streamer speech data, and 297,052 Danmaku messages from Douyin, this study examines the effects and variations of different dimensions of real-time interaction on consumer purchasing behavior, providing managerial insights for both enterprises and Streamers. The findings indicate that: (1) Streamer Informational Interaction, Danmaku Informational Interaction, Danmaku Emotional Interaction, and User Participatory Interaction significantly positively influence consumer purchasing behavior, whereas excessive Streamer Emotional Interaction negatively affects it; (2) Product Category moderates the relationship between different dimensions of real-time interaction and consumer purchasing behavior; (3) Streamer Influence positively moderates the relationship between various dimensions of real-time interaction and consumer purchasing behavior.

Keywords

livestream e-commerce, real-time interaction, social influence theory, text analysis

1. Introduction

According to the 56th Statistical Report on China's Internet Development Status released by the China Internet Network Information Center, as of June 2025, the scale of online shopping users in China had reached 976 million. Among these users, 45.9% had made purchases after watching short videos or livestreams, with 57.8% of these purchases being unplanned. This data not only confirms the substantial user acquisition and conversion capabilities of livestream e-commerce but also reveals its unique mechanism to stimulate latent consumer demand and reshape consumer decision-making pathways, which constitutes the core focus of this research. How can Streamers leverage their creative strengths to optimize livestream communication techniques and interaction quality, thereby creating content that attracts users and stimulates their demand? How can enterprises utilize Streamers and live streaming platforms to enhance user retention and improve livestream performance?

Real-time interaction represents the core characteristic that distinguishes livestream e-commerce from traditional e-commerce. Unlike the image-text and short video formats of conventional shelf-based e-commerce, livestream e-commerce enables immediate interaction among consumers, Streamers, and fellow viewers within the virtual livestream space. Existing research has confirmed the crucial role of interactivity in livestream e-commerce. For instance, Tao et al. (2021) demonstrated that livestream interactivity influences consumer sentiment, thereby affecting purchasing behavior, while Yu et al. (2024) verified that Streamers' interactivity positively impacts consumers' purchase intention and behavior through their feelings of pleasure and arousal. Some scholars have attempted dimensional classification of interactivity to better reveal its operational mechanisms. For example, Liu et al. (2022) discovered that product, interpersonal, and promotional interactions in e-commerce livestreams affect consumer purchasing behavior. Current studies typically treat interactivity as either an attribute of livestreams or a characteristic of Streamers, examining it as one of many antecedent variables affecting purchase intention. However, there remains insufficient exploration of the impact mechanism of real-time interaction on consumer purchasing behavior from the multidimensional perspective of interactive content.

To address this research gap, this study investigates how different dimensions of real-time interaction influence consumer purchasing behavior by employing text analysis and empirical methods using authentic livestream data from Douyin. The theoretical contributions of this study include expanding the application value of social influence theory in livestream e-commerce consumer behavior research and providing new perspectives for understanding consumer behavior in this context. On a practical level, the research findings offer empirical evidence for Streamers to optimize interaction strategies and for enterprises to develop differentiated livestream solutions, thereby effectively enhancing livestream performance and promoting sustainable development in the livestream e-commerce industry.

2. Literature Review

Livestream e-commerce is an online marketing model wherein content creators with a certain level of online influence utilize livestreaming features provided by social media or dedicated platforms to interact with viewers and promote specific products. As an emerging marketing approach, livestream e-commerce is currently in a phase of rapid development, attracting significant attention from both industry practitioners and academic researchers. Existing studies primarily focus on user engagement behavior and purchasing behavior.

2.1 Research on Consumer Purchasing Behavior in Livestream E-commerce Based on User-Generated Content

In livestream e-commerce, consumers have transformed from passive recipients of information into participatory stakeholders with voice and agency. Their engagement behaviors directly reflect their consumption intentions and preferences, with active user participation leading to positive marketing outcomes such as sales growth, enhanced competitive advantage, and improved profitability. Previous research has confirmed that user-generated content gradually becomes a crucial factor influencing other users' purchase decisions. As a form of user-generated content on livestream e-commerce platforms, Danmaku has been studied by Gao et al. (2021), who found that the mutual assistance nature of Danmaku influences viewers' sense of social presence, thereby affecting their livestream purchase inclination. Liu et al. (2023) discovered that the information quality of Danmaku affects consumers' perceived utilitarianism and sense of belonging, consequently influencing their purchase intention. Compared with questionnaire surveys, scholars are gradually shifting toward mining and analyzing authentic Danmaku texts. Zhou et al. (2019). indicated that the word count in Danmaku reflects the sense of presence during livestreams and positively influences consumers' gifting behavior. Han et al. (2022) found that the information richness and emotional polarity of Danmaku positively affect product sales in livestream e-commerce. In summary, existing literature recognizes the significance of Danmaku texts, confirming that both the quantity of Danmaku and its emotional characteristics can influence consumer purchasing behavior.

2.2 Research on Consumer Purchasing Behavior in Livestream E-commerce Based on Streamer Characteristics

In livestream shopping, the occurrence of consumer purchasing behavior relies more heavily on e-commerce Streamers as external cues. Research on e-commerce Streamers primarily falls into two categories: First, Streamer characteristics, where scholars often analyze Streamer attributes through the SOR theoretical framework, categorizing them into four aspects: expertise, attractiveness, interactivity, and credibility. For instance, Streamer characteristics in food livestreaming significantly positively influence consumers' psychological ownership, thereby positively affecting their impulse purchase intention (Gao et al., 2024). Han et al. (2020) proposed that e-commerce Streamer attributes significantly impact consumers' online purchase intention. Second, Streamer linguistic content. E-commerce Streamer language and communication techniques represent a spoken register distinct from written forms. Wang et al. (2022) summarized Streamer linguistic content characteristics into informational, entertainment, and quality aspects, finding that these characteristics positively influence consumers' perceived value, subsequently affecting purchase intention. Shi et al. (2024) demonstrated that Streamers' positive emotional communication, negative emotional communication, and cognitive communication positively influence consumers' livestream purchasing behavior, with interactive effects existing between these factors. In summary, existing research confirms that Streamers exert direct and significant influence on consumers' purchase decisions.

In conclusion, while existing literature has made considerable progress in examining how Streamer characteristics and user participation behaviors influence consumer purchasing behavior, it has predominantly treated "interactivity" merely as an attribute of livestreams or a trait of Streamers. Alternatively, studies have focused solely on the impact of Danmaku. This approach has led to a simplified and static understanding of real-time interaction, failing to reveal the differential effects of various dimensions within real-time interaction on consumer behavior.

3. Theoretical Analysis and Research Hypotheses

3.1 Theoretical Model

In the context of livestream e-commerce, consumers within the enclosed space of a livestream room are influenced by both the Streamer and other users, leading to changes in their attitudes and behaviors. Based on Social Influence Theory, this paper defines the specific components of real-time interaction into two categories: Streamer guidance, initiated by the Streamer through content information, and user interaction, constituted by user feedback through content information. Streamer guidance focuses on the most decisive and precisely measurable linguistic behaviors. Through Persuasion Theory, Streamers exert external influence at two levels: informational interaction and emotional interaction.

Grounded in Use and Gratifications Theory, users actively participate in interactions to fulfill their informational, emotional, and social needs. Therefore, this study examines the impact of these two categories of influencing factors—Streamer guidance and user interaction—on consumer purchasing behavior from the perspective of real-time interaction. Concurrently, existing research has demonstrated significant differences in the influence pathways between Streamers with high and low levels of influence, and consumers' value drivers also vary when making purchasing decisions for different types of products. This paper incorporates these as moderating variables. Furthermore, given the potential effects of information load, seller score, product price, and monthly live sessions on consumer purchasing behavior, these factors are included as control variables. The research model is illustrated in **Figure 1**.

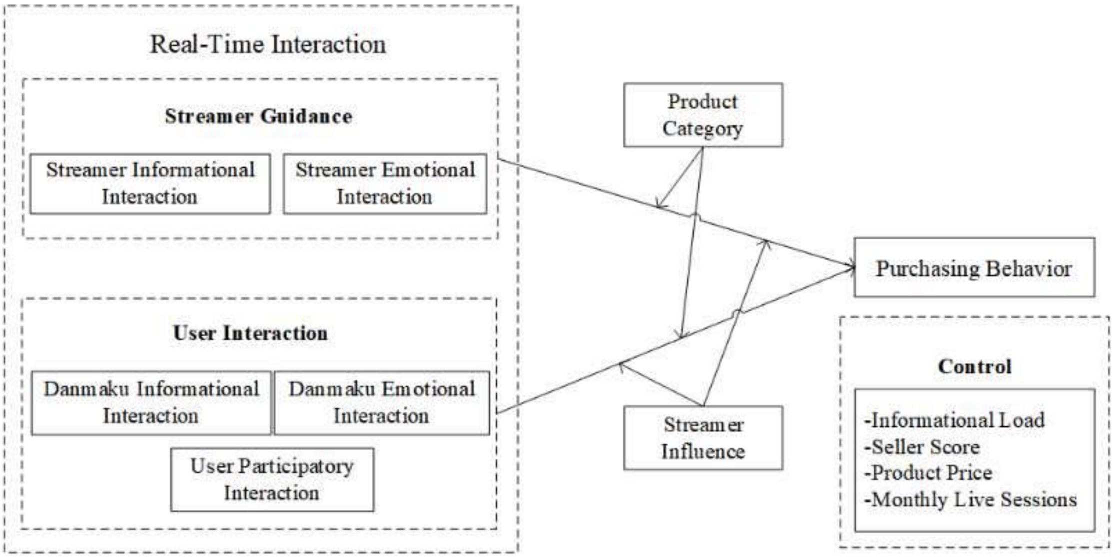

Figure 1. Research Model

3.2 Research Hypotheses

3.2.1 The Relationship between Streamer Guidance and Consumer Purchasing Behavior

During the persuasion process, when a persuader effectively conveys information, it generates trust in the recipient and makes them more inclined to accept their viewpoint (Pezzuti et al., 2021). Strong emotional expression by the persuader can narrow the psychological distance between the persuader and the recipient, making the information appear more relaxed and easier to accept. Sheng et al. (2022) pointed out that Streamers utilizing persuasive informational content can effectively transmit product information and positive emotions, thereby influencing consumers' cognition and emotions, and enhancing their online purchase intention. Therefore, the following hypotheses are proposed:

H1a: Streamer Informational Interaction positively influences consumer purchasing behavior;

H1b: Streamer Emotional Interaction positively influences consumer purchasing behavior.

3.2.2 The Relationship between User Interaction and Consumer Purchasing Behavior

Mutual assistance among viewers in livestream rooms influences consumers' perceived usefulness, perceived risk, and perceived psychological distance, thereby promoting their livestream participation intention (Xue, J. et al., 2020). Real-time Danmaku represents the transmission of users' personal emotions and expression of inner resonance. Existing research has confirmed that characteristics of

Danmaku interaction—such as quantity, information richness, degree of social interaction, and emotional polarity—affect consumer purchasing behavior to varying degrees (Chen et al., 2025). Jiang et al. (2022) proved that consumer participation significantly influences their purchasing behavior by utilizing large-scale livestream data. In the context of livestream e-commerce, increased interaction between users and Streamers or among users themselves enhances perceived value. Therefore, the following hypotheses are proposed:

H2a: Danmaku Informational Interaction positively influences consumer purchasing behavior.

H2b: Danmaku Emotional Interaction positively influences consumer purchasing behavior.

H2c: User Participatory Interaction positively influences consumer purchasing behavior.

3.2.3 The Moderating Role of Product Category

Different product attributes trigger distinct cognitive patterns and decision-making pathways in consumers. According to product classification theory, products can be categorized as utilitarian or hedonic. Utilitarian products are characterized by their instrumental and functional nature, with consumption behavior primarily driven by performance expectations. In this context, Streamers provide professional information, while Danmaku information serves as effective supplementary knowledge, helping consumers internalize information and make rational judgments, thereby significantly enhancing purchase intention. Hedonic products, conversely, emphasize emotional experiences and sensory pleasure. Consumers tend to rely on others' feelings and social cues to make judgments. Streamers' emotional expressions can stimulate consumers' affective discrimination thinking, promoting self-construction and emotional immersion. Meanwhile, user interaction not only evokes emotional resonance but also effectively reduces the perceived risk associated with product intangibility, thereby strengthening purchase motivation. Consequently, the following hypotheses are proposed:

H3a: Compared to hedonic products, the positive impact of Streamer Informational Interaction on consumer purchasing behavior is more pronounced for utilitarian products.

H3b: Compared to utilitarian products, the positive impact of Streamer Emotional Interaction on consumer purchasing behavior is more pronounced for hedonic products.

H3c: Compared to hedonic products, the positive impact of Danmaku Informational Interaction on consumer purchasing behavior is more pronounced for utilitarian products.

H3d: Compared to utilitarian products, the positive impact of Danmaku Emotional Interaction on consumer purchasing behavior is more pronounced for hedonic products.

H3e: Compared to utilitarian products, the positive impact of User Participatory Interaction on consumer purchasing behavior is more pronounced for hedonic products.

3.2.4 The Moderating Role of Streamer Influence

Streamer Influence refers to the degree of popularity and appeal a streamer possesses. According to existing research, streamer influence is typically measured by their follower count and serves as a crucial moderating variable in livestream e-commerce. Empirical studies have demonstrated that streamer influence plays a significant moderating role in how streamers' emotional language affects viewers' purchasing and liking behaviors in the context of livestream e-commerce (Chen et al., 2025). When a streamer possesses high influence, users tend to place greater trust in the streamer. Consequently, the product information they convey is more readily trusted by consumers, and they can more effectively evoke emotional resonance, thereby enhancing purchase intention. Higher user trust in the streamer strengthens their willingness to participate. In livestream sessions Steamered by high-influence streamers, consumers are more inclined to follow group behaviors, significantly improving the conversion efficiency from interaction to purchase. Therefore, the following hypotheses are proposed:

H4a: Streamer Influence positively moderates the effect of Streamer Informational Interaction on consumer purchasing behavior.

H4b: Streamer Influence positively moderates the effect of Streamer Emotional Interaction on consumer purchasing behavior.

H4c: Streamer Influence positively moderates the effect of Danmaku Informational Interaction on consumer purchasing behavior.

H4d: Streamer Influence positively moderates the effect of Danmaku Emotional Interaction on consumer purchasing behavior.

H4e: Streamer Influence positively moderates the effect of User Participatory Interaction on consumer purchasing behavior.

4. Data and Variables

4.1 Data Sources and Processing

The data for this study were sourced from the Douyin platform and third-party livestream monitoring services (https://dy.huitun.com/, https://m.kaogujia.com/). As of March 2025, Douyin's monthly active user base has exceeded 1 billion, maintaining its position as the leading short-video and livestream platform in China. The dataset primarily comprises livestream video data, livestream room attributes, and real-time user interaction data. The livestream video data were obtained directly from Douyin. This study selected 120 livestreams from the Huitun Real-time Livestream Ranking as research subjects, covering product categories such as 3C digital appliances, home electronics, and apparel/underwear. To mitigate potential biases from data collection at different times, all livestream recordings were consistently conducted between 8:00 PM and 11:00 PM. Based on research requirements, samples with missing Streamer audio were excluded, resulting in 83 valid video clips. Livestream room attribute data were collected from the Huitun platform, including livestream ID, follower count, seller score, monthly live sessions, product category, and product price. User real-time interaction data were obtained from the Kaogujia and Huitun platforms, encompassing Danmaku timestamps, content, quantity, viewer count, likes, and transactions per thousand views. The dataset incorporates three data formats: video, text, and numerical values.

To analyze consumer purchasing behavior at a more granular temporal level, this study conducted data preprocessing following the acquisition of raw data, including data transformation and data integration. During the data transformation phase, speech recognition technology was employed to convert the Streamer's speech from each minute of every livestream into textual data. In the data integration phase, minute-level Streamer speech text data and user real-time interaction data were matched according to the specific livestream session and corresponding timestamp. Specifically, the Streamer's speech text data for the Nth minute of a livestream was aligned with the user interaction data from the same minute. This process ultimately yielded a structured, real-time dynamic dataset comprising 9,684 minutes of observations, containing 2,953,829 words of Streamer speech text data and 297,052 Danmaku messages.

In this study, the keywords from both Danmaku content and Streamer speech content were statistically analyzed based on their frequency, with the top 300 keywords visualized in the word cloud shown in **Figure 2** and **Figure 3**. In the figure, larger font sizes indicate higher word frequencies. The keywords in livestream Danmaku texts reflect users' emotional resonance and positive feedback toward the livestream content. Meanwhile, Streamer language employs transaction-oriented vocabulary to clearly convey promotional information and action cues, addressing user concerns and reinforcing their purchase motivation.

Figure 2. Word Cloud Visualization of Keywords from Danmaku

Figure 3. Word Cloud Visualization of Keywords from Streamer Speech Texts

4.2 Variable Definitions and Measurement

4.2.1 Dependent Variable

This study employs minute-level transactions per thousand views to measure consumer purchasing behavior (PB) in livestream contexts, accurately assessing the actual effectiveness of livestream marketing. The calculation formula is shown in Equation (1):

$$\mathrm{PB} = \frac{\text{Actual Sales Volume}}{\text{Minute Viewership}} \times 1000 \tag{1}$$

4.2.2 Independent Variables

(1) Streamer Informational Interaction and Streamer Emotional Interaction

Streamer Informational Interaction (SII) and Streamer Emotional Interaction (SEI) are calculated using the Linguistic Inquiry and Word Count (LIWC) software. The tool operates by automatically identifying and calculating the proportion of words across different dimensions within a text through its built-in psycholinguistic dictionary, thereby revealing the underlying social, cognitive, and emotional processes embedded in the language (Pennebaker et al., 1999). This study adopts the latest official version, LIWC-22, to analyze the percentage scores of informational interaction words and emotional interaction words in the Streamer's speech, as shown in Equations (2) and (3). This relative frequency calculation method enables scientifically valid and comparable measurements across texts of varying lengths.

$$\text{SII}=\frac{\text{Number of Informational Interaction Words}}{\text{Total Word Count}}\times 100\% \tag{2}$$

$$\text{SEI}=\frac{\text{Number of Emotional Interaction Words}}{\text{Total Word Count}}\times 100\% \tag{3}$$

(2) Danmaku Informational Interaction

Danmaku Informational Interaction (DII) is reflected in Danmaku texts through references to and inquiries about product entities, attributes, and quantities. The calculation method involves part-of-speech tagging using text analysis techniques to compute the total frequency of nouns, numerals, modal particles, interrogative words, and English words in the minute-level Danmaku content, as shown in Equation (4):

$$\text{DII}=\text{Total Count of Informational Interaction Words} \tag{4}$$

(3) Danmaku Emotional Interaction

Danmaku Emotional Interaction (DEI) refers to the emotional attitudes conveyed by consumers in Danmaku messages regarding livestream content. The calculation method employs the sentiment analysis module of Baidu AI Open Platform's Natural Language Processing toolkit to determine the sentiment value of Danmaku messages. Existing research has validated the effectiveness of using Baidu AI Open Platform for sentiment analysis in e-commerce sales and product analysis studies. Specifically, this study utilizes API calls to automatically identify the sentiment value of each Danmaku message, then calculates the average sentiment value per minute to measure the minute-level Danmaku Emotional Interaction.

(4) User Participatory Interaction

User Participatory Interaction (UPI) serves as a core metric for gauging user engagement during livestream sessions. This study employs a composite indicator for its definition and measurement, integrating the minute-level Danmaku count and like increment while accounting for the current viewers in the livestream room. This approach enables equitable comparisons across livestream rooms of varying traffic levels and different time periods, accurately reflecting the real-time average engagement level of viewers. The calculation formula is shown in Equation (5):

$$\text{UPI}=\frac{\text{Danmaku Count+Minute-Level Like Increment}}{\text{current viewers}} \tag{5}$$

4.2.3 Moderating Variables

This study incorporates Streamer Influence (SI) and Product Category (PC) as moderating variables to examine their potential effects on the relationships between independent and dependent variables. Following established research practices (Diao et al., 2023), streamer influence is measured using the objective and quantifiable metric of follower count. For product categorization, this study classifies goods such as 3C digital appliances, fresh produce, and smart home devices as utilitarian products, while cosmetics, skincare items, jewelry, antiques, toys, and musical instruments are categorized as hedonic products. These categories are quantified using a binary dummy variable (utilitarian products coded as 1, hedonic products coded as 0).

4.2.4 Control Variables

To better validate the research hypotheses and account for potential endogenous and exogenous variables, this study controls for several potential influencing factors by referencing commonly used control variables in relevant literature. These include:

(1) Information Load (IL): Refers to the density of linguistic information conveyed by the Streamer per unit of time, quantified by the number of effective words output by the Streamer per minute.

(2) Seller Score (SS): Derived from the Streamer's historical livestream performance in terms of product quality, promotional authenticity, and service reliability, this metric preemptively influences users' initial trust levels and interaction tendencies upon entering the livestream. The score is obtained from the Huitun data platform as of the livestream date.

(3) Product Price (PP): As a core economic factor affecting consumers' perceived value and payment willingness, product price directly and critically influences final purchase decisions. This study uses the average product price per livestream session for measurement.

(4) Monthly Live Sessions (MLS): Reflects the Streamer's livestream activity intensity and content update frequency within a specific period, measured by the number of livestream sessions conducted by the Streamer in the current month, directly obtained from the Huitun data platform.

The measurement descriptions of the variables are presented in **Table 1**.

Table 1. Variable Measurement Descriptions

Variable Type	Variable Name	Abbreviation	Measurement Description
Dependent Variable	Purchasing Behavior	PB_{it}	Transactions per thousand views
Independent Variables	Streamer Informational Interaction	SII_{it}	Percentage of informational interaction words in Streamer's speech
	Streamer Emotional Interaction	SEI_{it}	Percentage of emotional interaction words in Streamer's speech
	Danmaku Informational Interaction	DII_{it}	Total count of informational interaction words in Danmaku
	Danmaku Emotional Interaction	DEI_{it}	Average sentiment value of Danmaku per minute
	User Participatory Interaction	UPI_{it}	(Like increment + Danmaku count)/current viewers per minute

Moderating Variables	Product Category	PC_i	Utilitarian products coded as 1, hedonic products coded as 0
	Streamer Influence	SI_i	Streamer's follower count at livestream start
Control Variables	Information Load	IL_{it}	Word count of Streamer's speech per minute
	Seller Score	SS_i	Seller reputation score
	Product Price	PP_i	Average transaction price per livestream session
	Monthly Live Sessions	MLS_i	Total number of livestream sessions conducted by Streamer per month

5. Empirical Analysis and Results

5.1 Descriptive Statistics and Standardization

The descriptive statistical analysis results of the variables are presented in **Table 2**. Significant differences in dimension and magnitude exist among the variables. To ensure the reliability of the results, standardization of the original indicator data is necessary. This study applied the z-score standardization method to standardize all explained variables.

Table 2. Descriptive Statistical Analysis

Variable Name	Minimum	Maximum	Mean	Standard Deviation	Median
Purchasing Behavior	13	214223	13943.321	27363.404	3023.5
Streamer Informational Interaction	0	33.86	14.309	4.638	14.29
Streamer Emotional Interaction	0	23.68	5.751	2.723	5.5
Danmaku Informational Interaction	0	754	60.736	64.274	41
Danmaku Emotional Interaction	0	1	0.46	0.189	0.48
User Participatory Interaction	0	5.968	0.288	0.432	0.166
Streamer Influence	7687	57022000	9018974.769	11891375.53	3445000

Seller Score	0	5	4.741	0.857	4.9
Monthly Live Sessions	1	68	27.088	13.799	29
Information Load	3	540	305.022	86.089	317
Product Category	0	1	0.492	0.5	0
Product Price	30	4700	306.69	565.109	150

5.2 Correlation Analysis and Multicollinearity Testing

To prevent potential bias in regression results due to multicollinearity, this study conducted correlation tests and variance inflation factor (VIF) tests on the independent, moderating, and control variables. The results are presented in **Table 3**. The maximum Pearson correlation coefficient among the variables is 0.32, which is below the 0.500 threshold, indicating low inter-variable correlations and relative independence between them. The maximum variance inflation factor (VIF) for all variables is 1.258, which is below 10, suggesting that multicollinearity has minimal impact and the model regression results are robust.

Table 3. Pearson Correlation and Multicollinearity Tests of Standardized Variables

	S_SI	S_SS	S_MLS	S_IL	S_PP	S_SII	S_SEI	S_DII	S_DEI	S_UPI
S_SI	1									
S_SS	0.168**	1								
S_MLS	0.190**	0.183**	1							
S_IL	-0.169**	-0.084**	0.112**	1						
S_PP	-0.188**	0.066**	0.097**	0.075**	1					
S_SII	0.061**	-0.128**	-0.070**	0.189**	0.009	1				
S_SEI	0.051**	-0.035**	0.089**	0.136**	-0.01	0.320**	1			
S_DII	0.042**	0.102**	-0.154**	-0.147**	0.014	0.046**	-0.025*	1		
S_DEI	0.191**	0.015	-0.034**	-0.089**	0.186**	-0.016	-0.039**	0.191**	1	
S_UPI	0.070**	0.079**	0.019	0.080**	0.134**	-0.062**	0.091**	0.012	0.035**	1
VIF	1.258	1.107	1.168	1.146	1.162	1.213	1.153	1.1	1.151	1.064

5.3 Regression Analysis

This study employs a negative binomial regression as the econometric model for the following reasons: (1) The dependent variable, measured by minute-level transactions per thousand views, constitutes non-negative count data suitable for count regression models; (2) The variance of the dependent variable significantly exceeds its mean, indicating over-dispersion that violates the Poisson distribution's equidispersion assumption, thus justifying the use of negative binomial regression. Additionally, the model accounts for both time-fixed effects and individual-fixed effects.

5.3.1 Direct Effect Tests of Different Dimensions of Real-Time Interaction

Model 1 includes all independent variables and control variables, as shown in Equation (6):

$$Log(PB_{it})=\beta_0+\beta_1 SII_{it}+\beta_2 SEI_{it}+\beta_3 DII_{it}+\beta_4 DEI_{it}+\beta_5 UPI_{it}+\beta_6 PP_i+\beta_7 SS_i+\beta_8 MLS_i+\beta_9 IL_{it} \tag{6}$$

The regression results are presented in Table 4. The findings indicate that the likelihood ratio test for the negative binomial regression is significant ($\chi^2(11)=6735.881, p=0.000$), demonstrating a good model fit. Furthermore, streamer informational interaction, Danmaku informational interaction, Danmaku emotional interaction, and user participatory interaction all exhibit significant positive effects on consumer purchasing behavior, supporting hypotheses H1a, H2a, H2b, and H2c. Conversely, streamer emotional interaction demonstrates a significant negative impact on consumer purchasing behavior, leading to the rejection of hypothesis H1b.

5.3.2 Moderating Effect Test of Product Category

The sample was divided into two groups based on product category to examine how product type moderates the relationship between different dimensions of real-time interaction and purchasing behavior in livestream e-commerce. Model 2 in **Table 4** presents the regression results for hedonic products, while Model 3 shows the results for utilitarian products. The results indicate that the likelihood ratio test for Model 2 is significant ($\chi^2(11)=2891.793$, $p=0.000$), and similarly significant for Model 3 ($\chi^2(11)=5240.935$, $p=0.000$). The notable decrease in AIC and BIC values further confirms good model fit. The positive effects of streamer informational interaction and Danmaku informational interaction on consumer purchasing behavior are significantly stronger for utilitarian products than for hedonic products, supporting hypotheses H3a and H3c. Streamer emotional interaction negatively affects consumer purchasing behavior for both product types, with consumers being particularly sensitive to this factor in hedonic product decisions, leading to the rejection of hypothesis H3b. Danmaku emotional interaction shows a significant positive impact on hedonic products but no significant effect on utilitarian products, supporting hypothesis H3d. User participatory interaction significantly promotes purchasing behavior for hedonic products while significantly inhibiting it for utilitarian products, supporting hypothesis H3e.

Table 4. Negative Binomial Regression Results of Different Real-Time Interaction Dimensions on Consumer Purchasing Behavior

Dependent Variable：PB	Model 1	Model 2(PC=0)	Model 3(PC=1)
Variable	Coefficient	Coefficient	Coefficient
S_SII	0.318** (28.567)	0.104** (6.875)	0.476** (28.580)
S_SEI	-0.093** (-8.511)	-0.196** (-12.826)	-0.034* (-2.087)
S_DII	0.482** (44.998)	0.302** (17.819)	0.419** (26.130)
S_DEI	0.156** (14.734)	0.227** (15.290)	0.024 (1.535)
S_UPI	0.094** (8.816)	0.308** (20.478)	-0.413** (-26.145)
Control Variables	Yes	Yes	Yes
Individual Fixed Effects		Yes	
Time Fixed Effects		Yes	
Likelihood Ratio Test	$\chi^2(11)$=6735.881	$\chi^2(11)$=2891.793	$\chi^2(11)$=5240.935
AIC	197480.909	93971.231	101147.813
BIC	-68807.566	-31087.462	-33301.288
N	9684	4764	4920

Note. * p<0.05 ** p<0.01.

5.3.3 Moderating Effect Test of Streamer Influence

This study employed hierarchical regression analysis to examine the moderating effect of streamer influence on the relationship between different dimensions of real-time interaction and consumer purchasing behavior. Model 4 builds upon Model 1 by incorporating streamer influence, while Model 5 further adds five interaction terms formed between streamer influence and real-time interaction dimensions, as shown in Equation (7):

$$\begin{aligned}\mathrm{Log}(\mathrm{PB_{it}}) = {} & \beta_0 + \beta_1\mathrm{SII_{it}} + \beta_2\mathrm{SEI_{it}} + \beta_3\mathrm{DII_{it}} + \beta_4\mathrm{DEI_{it}} + \beta_5\mathrm{UPI_{it}} + \beta_6\mathrm{PP_i} + \beta_7\mathrm{SS_i} + \beta_8\mathrm{MLS_i} \\ & + \beta_9\mathrm{IL_{it}} + \beta_{10}\mathrm{SI_i} + \beta_{11}(\mathrm{SI_i} \times \mathrm{SII_{it}}) + \beta_{12}(\mathrm{SI_i} \times \mathrm{SEI_{it}}) + \beta_{13}(\mathrm{SI_i} \times \mathrm{DII_{it}}) + \beta_{14}(\mathrm{SI_i} \\ & \times \mathrm{DEI_{it}}) + \beta_{15}(\mathrm{SI_i} \times \mathrm{UPI_{it}})\end{aligned} \tag{7}$$

The regression results presented in **Table 5** demonstrate that streamer influence exerts a significant positive effect on consumer purchasing behavior (β=0.801, p<0.001). Model 5 shows a significant likelihood ratio test ($\chi^2(17)$=11521.584, p=0.000) with decreased AIC and BIC values, indicating improved model fit. The interaction terms between real-time interaction dimensions and streamer influence show significant positive correlations with consumer purchasing behavior, confirming the positive moderating role of streamer influence in the relationship between various real-time interaction dimensions and purchasing behavior. Thus, hypotheses H4a-H4e are fully supported. However, the direct effect reveals a negative relationship between streamer emotional interaction and consumer purchasing behavior. This suggests that as streamer influence increases, the negative impact of streamer emotional interaction on purchasing behavior is significantly attenuated.

Table 5. Negative Binomial Regression Results of the Moderating Effect of Streamer Influence

Dependent Variable：PB	Model 4	Model 5
Variable	Coefficient	Coefficient
S_SII	0.163** (14.311)	0.154** (13.685)
S_SEI	-0.136** (-12.480)	-0.144** (-13.130)
S_DII	0.500** (46.723)	0.489** (43.575)
S_DEI	0.052** (4.746)	0.031** (2.827)
S_UPI	0.260** (24.243)	0.153** (13.461)
S_SI	0.801** (68.693)	0.738** (60.623)
SI*SII		0.023* (2.118)
SI*SEI		0.089** (8.148)
SI*DII		0.066** (4.847)
SI*DEI		0.082** (7.498)
SI*UPI		0.322** (25.721)
Likelihood Ratio Test	$\chi^2(17)=10909.192$	$\chi^2(17)=11521.584$
AIC	193309.599	192707.206
BIC	-72971.698	-73538.2
N	9684	9684

5.4 Robustness Tests

To ensure the reliability of the research findings, this study conducted a robustness test by replacing the composite metric of User Participatory Interaction with a single indicator—bullet chat count—and re-ran the regression analysis. The results are presented in **Table 6** and **Table 7**, which only displays the regression coefficients of the independent variables for clarity. The findings demonstrate that the significance levels and directional effects of the core variables remain consistent with the original regression results, thereby confirming the robustness of the earlier conclusions.

Table 6. Robustness Test Results

Dependent Variable：PB	Model 1	Model 2(PC=0)	Model 3(PC=1)
Variable	Coefficient	Coefficient	Coefficient
S_SII	0.361** (32.655)	0.212** (13.914)	0.431** (26.144)
S_SEI	-0.085** (-7.861)	-0.234** (-15.629)	-0.028 (-1.738)
S_DII	0.049** (3.221)	0.044* (2.157)	0.383** (14.584)
S_DEI	0.095** (8.691)	0.039* (2.428)	0.184 (12.088)
S_UPI	0.575** (37.354)	0.585** (28.483)	-0.548** (-34.150)
Control Variables	Yes	Yes	Yes
Individual Fixed Effects		Yes	
Time Fixed Effects		Yes	
Likelihood Ratio Test	$\chi^2(11)=7559.588$	$\chi^2(11)=3166.983$	$\chi^2(11)=5463.411$
AIC	196657.203	93696.041	100925.337
BIC	-69631.273	-31362.652	-33523.764
N	9684	4764	4920

Table 7. Robustness Test-Moderating Effect of Streamer Influence

Dependent Variable：PB	Model 4	Model 5
Variable	Coefficient	Coefficient
S_SII	0.241** (21.571)	0.237** (20.997)
S_SEI	-0.146** (-13.479)	-0.142** (-13.093)
S_DII	0.057** (3.761)	0.167** (10.649)
S_DEI	0.005 (0.455)	0.022 (1.828)
S_UPI	0.558** (35.687)	0.480** (30.341)
S_SI	0.722** (61.627)	0.775** (58.503)
SI*SII		0.463** (34.499)
SI*SEI		0.082** (5.255)
SI*DII		0.467** (25.461)
SI*DEI		0.100** (9.147)
SI*UPI		0.047** (4.288)
Likelihood Ratio Test	$\chi^2(17)=11485.869$	$\chi^2(17)=12175.634$
AIC	192732.922	192053.157
BIC	-73548.375	-74192.249
N	9684	9684

6. Research Conclusions and Implications

6.1 Research Conclusions

The research findings of this study are as follows:

(1) Streamer informational interaction, Danmaku informational interaction, Danmaku emotional interaction, and user participatory interaction significantly positively influence consumer purchasing behavior, whereas streamer emotional interaction exerts a significant negative impact on consumer purchasing behavior. In the information-asymmetric environment of livestream e-commerce, Streamers providing professional knowledge regarding product functions, materials, and performance parameters directly fulfill consumers' cognitive needs. Danmaku messages supplement user experience information, assisting consumers in making purchasing decisions. The spontaneous emotional expressions in danmaku, due to their authenticity, effectively stimulate emotional resonance and herd mentality. User participatory interaction transforms the shopping process into a collective activity characterized by shared experiences, enhancing users' sense of immersion. These real-time interaction dimensions enable consumers to experience the value and enjoyment of livestream shopping, effectively promoting purchasing behavior. However, the highly homogenized emotional output by Streamers in current livestream rooms is easily perceived by consumers as sales tactics, raising doubts about their professionalism and credibility, ultimately suppressing purchase intention.

(2) Product category moderates the relationship between real-time interaction and consumer purchasing behavior. Specifically: For utilitarian products, both streamer informational interaction and danmaku informational interaction demonstrate stronger positive effects on purchasing behavior. In such contexts, consumer decision-making heavily relies on objective, professional information to reduce functional and financial risks. Streamer emotional interaction shows negative effects for both product types, indicating that excessive or formulaic enthusiasm is generally perceived as insincere, thereby damaging trust. Danmaku emotional interaction only exhibits significant positive impact for hedonic products, suggesting that atmospheric interaction must align with product emotional characteristics to be effective. User participatory interaction significantly promotes purchasing behavior for hedonic products while inhibiting it for utilitarian products. This indicates that for hedonic products, user participation enhances fun and engagement, effectively amplifying positive emotional experiences that facilitate purchase decisions. However, for utilitarian products, excessive bullet chats or likes disrupt consumers' coherent information processing, ultimately suppressing purchase intention.

(3) Streamer influence positively moderates the relationship between real-time interaction and consumer purchasing behavior. First, professional information conveyed by high-influence streamers is endowed with authoritative certification attributes, significantly enhancing consumers' adoption of such content. Simultaneously, their emotional expressions receive authenticity endorsement, effectively mitigating potential psychological resistance caused by perceived performative enthusiasm. Second, in livestream rooms streamered by high-influence streamers, user-generated content transcends fragmented individual opinions to become credible supplementary information, substantially stimulating consumers' herd mentality. This deep-level emotional engagement is efficiently converted into purchasing behavior.

6.2 Managerial Implications

The research findings of this study provide empirically grounded, refined operational strategies for key participants in the livestream e-commerce ecosystem. Specific practical implications are as follows:

(1) For streamers: On one hand, establishing standardized livestream terminology systems can enhance the structure and professionalism of product information delivery, thereby strengthening consumers' rational understanding of product features and building trust. On the other hand, given the empirically demonstrated negative impact of streamer emotional interaction on consumer purchasing behavior, streamers must carefully regulate the intensity and appropriateness of emotional expression. Excessive or artificial emotional appeals may trigger psychological resistance among consumers, so interaction processes should consistently support rational decision-making and maintain emotional comfort.

(2) For enterprises: Companies should strategically select livestream sales models to enhance overall marketing effectiveness. For utilitarian product brands, a professionalism-oriented approach is recommended, focusing on Streamers' professional qualifications and knowledge delivery capabilities, with priority given to vertical category influencers with authoritative endorsements in specific fields to meet consumers' information needs regarding objective product attributes. For hedonic product brands, an emotion-oriented strategy is more suitable, emphasizing the selection of high-influence Streamers with strong emotional appeal to create immersive shopping atmospheres that stimulate emotional resonance and herd mentality, thereby fulfilling consumers' emotional experience demands.

(3) For livestream platforms: Platforms can leverage big data to develop product-attribute-aware intelligent recommendation systems. For utilitarian product categories, algorithmic weights should prioritize cognitive metrics such as information density, professional depth, and parameter accuracy. For hedonic product categories, emphasis should be placed on emotional metrics including interaction frequency, emotional resonance, and atmospheric immersion. Platforms should establish multi-dimensional Streamer capability labeling systems and develop differentiated training mechanisms to guide Streamers toward professional specialization, thereby enhancing the matching efficiency among Streamers, products, and scenarios. Additionally, traffic support should be provided to professionally competent Streamers with limited follower bases to foster a healthy Streamer growth ecosystem.

6.3 Research Limitations and Future Directions

While this study employs a scientifically rigorous empirical process to investigate the impact of different dimensions of real-time interaction on consumer purchasing behavior, several limitations remain. First, the research data were sourced exclusively from the Douyin livestream platform, which may limit the generalizability of the findings. Future research could enhance external validity by comparing data from multiple livestream e-commerce platforms. Second, although the sentiment analysis of minute-level danmaku emotional interaction was conducted using Baidu AI Open Platform's NLP module—a method with demonstrated reliability—employing alternative sentiment analysis techniques could further strengthen the robustness of the conclusions. Future studies may validate these findings using different sentiment measurement approaches. Finally, this study primarily examines the direct effects of various real-time interaction dimensions on consumer purchasing behavior. The underlying mechanisms through which these dimensions influence purchasing decisions likely involve more complex mediating pathways. Future research should further explore the intrinsic mechanisms mediating the relationship between real-time interaction dimensions and consumer purchasing behavior.

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