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RESEARCH ARTICLE

Impacts of Bullet-Screen Content and Behavioral Characteristics on Consumer Purchasing Behavior in Live Streaming E-Commerce: Moderating Effect of Streamer-Product Relevance*

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Abstract

This paper investigates the effects of bullet-screen content and behavioral characteristics on consumer purchasing behavior in live streaming e-commerce, as well as the moderating effect of streamer-product relevance. Based on the Elaboration Likelihood Model (ELM), this paper uses bullet-screen data from the Douyin platform and consumer data from the Huitun platform. By combining text mining with zero-inflated negative binomial regression, this paper investigates the factors influencing consumer purchasing behavior from two perspectives: bullet-screen content characteristics as the central route and behavioral characteristics as the peripheral route. Grouped regression analysis is further employed to examine the moderating role of streamer-product relevance. Information richness, social interaction degree, and the number of bullet-screen comments positively affect purchasing behavior. The effect of the sentiment polarity of bullet-screen comments on purchasing behavior follows an inverted U-shaped pattern. Compared with live streaming rooms with low streamer-product relevance, those with high streamer-product relevance exhibit a broader range over which the sentiment polarity of bullet-screen comments positively affects purchasing behavior. This paper selects bullet-screen comments from only one live streaming e-commerce platform, and its findings therefore lack generalizability. Analyzing the factors influencing consumers' actual purchasing behavior from the perspective of bullet-screen comments can provide practical guidance and recommendations for effective communication between merchants and consumers and for improving sales effectiveness under the live streaming e-commerce model.

Keywords live streaming e-commerce; purchasing behavior; streamer-product relevance; bullet-screen characteristics; Elaboration Likelihood Model (ELM)

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1 Introduction

The rapid development of internet technology and emerging social media has made live streaming e-commerce an important part of the wider e-commerce landscape. Prominent examples include Amazon Live abroad, Douyin Live, and Taobao Live in China. According to the China Internet Network Information Center, the number of live streaming e-commerce users in China rose sharply from 309 million in June 2020 to 526 million in June 2023. As an emerging form of e-commerce, live streaming e-commerce platforms enable consumers to post bullet-screen comments in live streaming rooms and interact with both streamers and other consumers in real time (Zeng et al., 2023). These comments scroll continuously across prominent areas of the live streaming interface, facilitating the exchange of information and emotions, thereby helping to build positive relationships between buyers and sellers (Zhang et al., 2022). Bullet-screen comments have consequently become an important influence on consumer purchasing behavior (Han et al., 2022; Li et al., 2021).

Research on the effects of bullet-screen comments in live streaming e-commerce is still at an early stage and remains subject to substantial limitations. Firstly, existing studies have concentrated mainly on basic attributes, such as comment length and volume, and their effects on consumer behavior (Zhou et al., 2019). Far less attention has been paid to the semantic content of bullet-screen comments. Secondly, much of the existing evidence comes from questionnaires and interviews. The ways in which the content and behavioral characteristics of bullet-screen comments affect consumer purchasing behavior, and the boundary conditions governing these effects, therefore remain unclear.

To address these gaps, this paper uses actual live streaming data from Douyin and constructs a zero-inflated negative binomial regression model to examine how bullet-screen content and behavioral characteristics affect consumer purchasing behavior. Grouped regression analysis is also employed to test the moderating role of streamer-product relevance. Theoretically, this paper extends the application of the Elaboration Likelihood Model (ELM) to consumer purchasing behavior in live streaming e-commerce and introduces a new perspective for research on consumer behavior in this setting. Practically, its findings provide guidance for live streaming e-commerce platforms and streamers seeking to improve brand marketing and promotion and strengthen customer relationship management.

2 Literature Review

2.1 Consumer Purchasing Behavior in Live Streaming E-Commerce

Research on the determinants of consumer purchasing behavior in live streaming e-commerce has largely approached the subject from four perspectives: streamers, live streaming platforms, live streaming content, and consumers. Streamer-focused studies have generally relied on surveys to examine how streamers' personal characteristics and streamer-related match-ups shape consumers' purchase intention. For example, He and Jin (2024) find that the

attractiveness, trustworthiness, and expertise of key opinion leaders are positively associated with purchase intention. Park and Lin (2020) show that product-source fit significantly increased consumers' purchase intention. Research on live streaming platforms has likewise relied mainly on surveys and interviews to investigate how platform functions and technologies affect purchase intention. Wang et al. (2023) demonstrate that four coexisting information technology affordances, namely visibility, source diversity, interactivity, and entertainment, increased consumers' purchase intention. Sun et al. (2019) find that visibility affordance, metavoicing affordance, and guidance shopping affordance influenced purchase intention through live streaming engagement. Studies of live streaming content have instead used secondary data to assess its effects on consumer purchasing behavior. Yang et al. (2023) and Huo et al. (2025), for instance, find that social interaction-oriented information in streamers' live speech affects consumer purchasing behavior. Consumer-focused studies have generally used surveys to examine how consumers' personal characteristics and psychological factors shape the shopping process. Addo et al. (2021) find a significant association between customer engagement and purchase intention. Tong et al. (2022) show that the emotional states of pleasure and arousal exhibit a mediating effect on the relationship between the background visual complexity of the live streaming room and purchase intention, with gender exerting a significant moderating effect.

Taken together, most existing studies have relied on questionnaire data. A growing number of scholars have therefore called for research using actual live streaming data to identify the factors shaping consumer purchasing behavior in live streaming e-commerce (Huo et al., 2025). Existing studies have also largely overlooked the effects of live streaming bullet-screen comments on purchasing behavior (Han et al., 2022; Zeng et al., 2023). Yet consumers are influenced not only by streamers but also by other consumers in the live streaming room (Meng et al., 2021). Examining the effects of bullet-screen comments on consumer purchasing behavior is therefore necessary.

2.2 Effects of Bullet-Screen Comments

Research on the effects of bullet-screen comments has made some progress, but it has concentrated chiefly on basic characteristics, such as comment volume and word count, and their effects on consumption behavior. Zhou et al. (2019) find that the total number of words in bullet-screen comments captures the presence of others in a live stream and positively affects tipping. Chen et al. (2022) find that a larger volume of bullet-screen comments increased the view counts of bullet-screen videos. Advances in natural language processing have encouraged some scholars to examine the semantic content of bullet-screen comments, particularly their information richness and sentiment polarity (X. L. Wang et al., 2021). Han et al. (2022) find that peaks in information richness and sentiment polarity positively affected product sales in live streaming e-commerce. Zeng et al. (2023) demonstrate an inverted U-shaped relationship between bullet-screen sentiment and

consumers' purchase intention.

Extant research has thus considered how both the basic characteristics and semantic content of bullet-screen comments affect online consumption behavior. Important gaps nevertheless remain. In particular, studies of semantic content have largely neglected social interaction. As social interaction is among the defining features of live streaming e-commerce (Huo et al., 2025), the classification of semantic content needs to be broadened. A comprehensive analysis should consider three dimensions: information richness, social interaction degree, and sentiment polarity of bullet-screen comments.

2.3 Elaboration Likelihood Model

The ELM is a social psychological theory of persuasion. It explains the internal mechanisms through which individuals form or change their attitudes when confronted with persuasive information (Petty & Cacioppo, 1986). According to the model, attitudes may be shaped through either a central or a peripheral route. The central route involves analyzing, considering, and integrating issue-relevant information, thereby producing attitude formation or change. It places the substance of the information at the center of the judgment process. The peripheral route, by contrast, does not require direct or extensive scrutiny of information content. Individuals instead rely on contextual cues associated with the information when making judgments, which may ultimately produce attitude formation or change (Zeng et al., 2022). Although attitudes can, in principle, be formed entirely through either route, individuals generally draw on both in practice (Sussman & Siegal, 2003).

The ELM has been widely used to study online decision-making and information processing. Wang et al. (2020), for example, identify idea content quality as a central cue affecting users' idea adoption, while user community status, user contribution behavior, and community identification acted as peripheral cues. Leong et al. (2019) apply the model to examine how perceived electronic word-of-mouth (eWOM) credibility, user expertise, and user involvement influenced hotel booking intention. Li et al. (2021) use it to investigate how the information processing of live streaming e-commerce viewers shapes their attitudes and purchase intention. The helpfulness of online reviews depends on central cues, including review depth, review polarity, and review timeliness, as well as the peripheral cue of reviewer expertise (Y. N. Wang et al., 2021).

The influence of bullet-screen comments on consumer purchasing behavior in live streaming e-commerce similarly involves online decision-making and information processing. The ELM is therefore well suited to examining this relationship. Live streaming bullet-screen comments also provide richer and more comprehensive information than traditional online reviews. The model should consequently be adapted and extended to reflect the distinctive context of live streaming e-commerce.

3 Research Hypotheses and Theoretical Model

3.1 Research Hypotheses

3.1.1 Effects of Central-Route Cues on Consumer Purchasing Behavior

The content characteristics of bullet-screen comments serve as central-route cues through which consumers process information in live streaming e-commerce. They therefore provide an important basis for purchasing behavior. This paper evaluates the effects of bullet-screen content characteristics on purchasing behavior along three dimensions: information richness, social interaction degree, and the sentiment polarity of bullet-screen comments. Information richness is the potential information-carrying capacity of a medium. It captures the medium's ability to clarify ambiguity within a given period and help the parties involved reach a shared understanding (Zhu et al., 2018). Richer information better satisfies consumers' needs to gather and evaluate information, reduces uncertainty surrounding purchase decisions, and thereby encourages purchasing behavior (Hu et al., 2012). Hu et al. (2012), for example, show that information richness significantly affects purchasing behavior across different shopping channels. He et al. (2014) find that website information richness increases purchase intention in the e-commerce of fresh agricultural products. Using data from a paid-knowledge platform, Fang et al. (2021) demonstrate that the information richness of extant reviews mitigates the negative effect of a free return policy on sales. In live streaming e-commerce, consumers can obtain product-related information in real time from bullet-screen comments posted by other consumers. This paper expects that the richer the product information contained in bullet-screen comments, the more effectively it will deepen consumers' understanding of the product and reduce their perceived uncertainty, thereby promoting their purchasing behavior. Accordingly, the following hypothesis is proposed.

H1: Information richness positively affects consumer purchasing behavior.

Social interaction degree refers to the extent to which people engage in social interaction to foster positive interpersonal relationships (Chen et al., 2009). Social content embedded in online information can strengthen trust, satisfaction, and commitment between individuals (Liang et al., 2011), thereby encouraging consumer purchasing behavior (Zhao et al., 2018). Yang et al. (2023) and Huo et al. (2025), for example, find that streamers convey social interaction-oriented content by greeting viewers and initiating social topics. Such content encourages consumers to participate in live streaming discussions and, in turn, facilitates consumption behavior. Ma et al. (2022) show that consumers engage in social interactions with streamers and other consumers by posting bullet-screen comments in live streaming rooms, which generates a sense of social presence and consequently influences their trust and purchasing behavior. The use of socially oriented language in bullet-screen comments can also strengthen relational bonds between streamers and consumers (Hu & Chaudhry, 2020), further encouraging purchases.

H2: Social interaction degree positively affects consumer purchasing behavior.

The sentiment polarity of bullet-screen comments captures the emotional attitudes that consumers express toward live streaming content and products (Han et al., 2022). Emotionally

valenced comments enable viewers to exchange emotions in real time. Because viewers are susceptible to the emotions expressed by others (Han et al., 2022), these exchanges can shape their attitudes toward and choices concerning the content and products presented in a live stream (Tsai et al., 2020). As bullet-screen comments become more positive, consumer attitudes should also become more favorable, increasing the likelihood that consumers will purchase and recommend the products (Chevalier & Mayzlin, 2006). Yet excessive positivity may prove counterproductive. Once the sentiment polarity of bullet-screen comments passes a certain threshold, consumers may question the authenticity of the comments (Berger et al., 2010). Such skepticism reduces the comments' perceived helpfulness (Zeng et al., 2023) and weakens purchase intention. The relationship between the sentiment polarity of bullet-screen comments and purchasing behavior should therefore be nonlinear. Consistent with this reasoning, Zeng et al. (2023) identify an inverted U-shaped relationship between bullet-screen sentiment and consumer purchase intention. Accordingly, the following hypothesis is proposed.

H3: The sentiment polarity of bullet-screen comments has an inverted U-shaped relationship with consumer purchasing behavior.

3.1.2 Effects of Peripheral-Route Cues on Consumer Purchasing Behavior

The behavioral characteristics of bullet-screen comments serve as peripheral-route cues through which consumers process information in live streaming e-commerce. They, too, provide an important basis for purchase decisions. The number of bullet-screen comments reflects both the intensity of consumer participation and the perceived presence of others in a live streaming room (Han et al., 2022). This paper therefore uses comment volume to capture bullet-screen behavioral characteristics. The number of bullet-screen comments is the total number of comments posted by consumers per unit of time. As this number rises, consumers perceive a stronger presence of others and experience greater psychological arousal (Zhou et al., 2019), making a purchase decision more likely. Bullet-screen comments also allow consumers to express opinions, ask questions, and obtain immediate answers from other viewers. A higher comment volume thus gives consumers access to more product information and strengthens their purchase intention. Zeng et al. (2023) find that the number of bullet-screen comments positively affects purchase intention in live streaming e-commerce. Du and Huang (2025) show that the number of bullet-screen comments partially mediates the relationship between influencer happiness intensity and sales. Accordingly, the following hypothesis is proposed.

H4: The number of bullet-screen comments positively affects consumer purchasing behavior.

3.1.3 Moderating Role of Streamer-Product Relevance

Consumers tend to focus more heavily on the product when streamer-product relevance

is high and more heavily on the streamer when such relevance is low (Huo et al., 2025). Perceiving a product as important places consumers in a state of high involvement (Flynn & Goldsmith, 1993). Consumers in live streaming rooms with high streamer-product relevance should therefore exhibit greater involvement. Zhang et al. (2016) propose that highly involved consumers devote more time and cognitive effort to evaluating information content, whereas consumers with low involvement are unwilling to spend excessive time evaluating such content. Consequently, the factors affecting purchasing behavior differ significantly between consumers at different levels of involvement. For example, Park et al. (2007) find that when consumers have high product involvement, their purchase decisions depend more heavily on information content, such as review quality. When consumers have low product involvement, their purchase decisions depend more heavily on intuitive cues, such as review quantity. Qi et al. (2021) note that users purchasing utilitarian paid-knowledge products are in a state of high product involvement and pay greater attention to information quality. By contrast, users purchasing hedonic paid-knowledge products are in a state of low product involvement and pay greater attention to information source credibility. In live streaming e-commerce, consumers in live streaming rooms with high streamer-product relevance are highly involved and adopt a systematic approach to information processing (Zhang et al., 2016). They therefore depend more heavily on the central route when processing the content information conveyed by bullet-screen comments. By contrast, consumers in live streaming rooms with low streamer-product relevance have low involvement and adopt a relatively simple approach to information processing and evaluation (Kardes et al., 2004). They therefore depend more heavily on the peripheral route when processing information about bullet-screen behavior. Accordingly, the following hypotheses are proposed.

H5a–H5c: Along the central route, the positive effects of bullet-screen information richness, social interaction degree, and sentiment polarity on consumer purchasing behavior are more pronounced in live streaming rooms with high streamer-product relevance than in those with low streamer-product relevance.

H5d: Along the peripheral route, the positive effect of the number of bullet-screen comments on consumer purchasing behavior is more pronounced in live streaming rooms with low streamer-product relevance than in those with high streamer-product relevance.

3.2 Theoretical Model

The ELM posits that central-route and peripheral-route cues jointly shape individual attitude change (Petty & Cacioppo, 1986). Research in live streaming e-commerce has shown that consumers process live streaming information through both routes when forming purchase intention (Zeng et al., 2023). This paper proposes that, when purchasing products in live streaming rooms, consumers process the content of bullet-screen comments through the central route while simultaneously processing information about bullet-screen behavior through the peripheral route. Previous studies have used information richness (Han

et al., 2022), social interaction degree (Huo et al., 2025; Yang et al., 2023), and the sentiment polarity of bullet-screen comments (Han et al., 2022; Zeng et al., 2023) as dimensions for measuring live-streaming content characteristics. Accordingly, this paper comprehensively considers information richness, social interaction degree, and sentiment polarity of bullet-screen comments when examining the content characteristics of bullet-screen comments in live streaming e-commerce. Previous research has also indicated that the number of bullet-screen comments reflects consumer activity (Han et al., 2022) and has been used to measure users' behavioral characteristics (Yang & Yu, 2022). Accordingly, this paper considers the number of bullet-screen comments when examining the behavioral characteristics of bullet-screen comments in live streaming e-commerce.

Based on differences in the associative link between an endorser and the endorsed product, Ilicic and Webster (2014) classify endorser-product relevance into high and low levels. In live streaming e-commerce, streamers assume the role of endorsers. Streamers who sell their own products over an extended period or promote only a single product therefore exhibit high streamer-product relevance, whereas those who promote multiple brands and products exhibit low streamer-product relevance (Wongkitrungrueng et al., 2020). Existing research has demonstrated that the mechanisms associated with high and low streamer-product relevance differ significantly. For example, Huo et al. (2025) propose that streamer-product relevance significantly moderates the relationships between relational social interaction-oriented content and consumers' tipping and purchasing behaviors. This paper expects the mechanisms through which bullet-screen content and behavioral characteristics affect consumer purchasing behavior to differ significantly between live streaming rooms with different levels of streamer-product relevance.

In summary, this paper constructs a model of the factors influencing consumer purchasing behavior in live streaming e-commerce, as shown in Figure 1. The model is intended to accurately identify the key factors influencing consumer purchasing behavior in live streaming e-commerce from the perspective of bullet-screen information processing.

4 Research Design

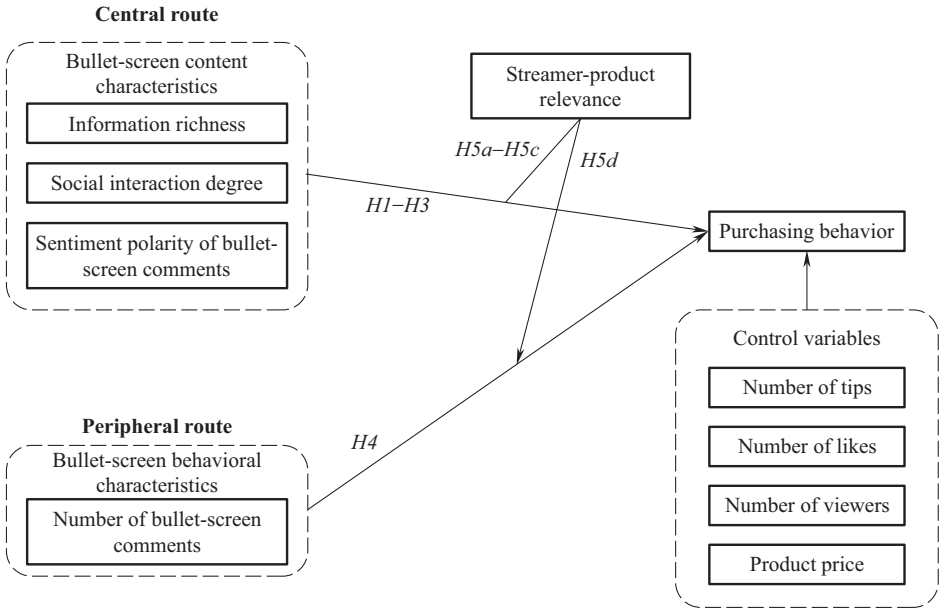
4.1 Data Collection

This paper uses live streaming e-commerce data from Douyin Live for two reasons. Firstly, Douyin is one of China's most popular live streaming e-commerce platforms, with 680 million monthly active users (Huo et al., 2025). The large user base supports the generalizability of the findings. Secondly, Douyin disabled external e-commerce links in live streaming rooms in October 2020. All product links have since been directed to Douyin Shops within the platform, creating a complete closed-loop e-commerce system and ensuring the completeness of product sales data (Han et al., 2022).

The dataset comprises two main components: bullet-screen data and consumer data. The bullet-screen data were collected from Douyin and include the content and posting time of

Figure 1

Research Model



each comment. A JavaScript-based web crawler was used to collect bullet-screen data from 834 live streams hosted by 724 streamers between September 26 and October 20, 2023. Table 1 presents the characteristics of the sample.

Table 1

Descriptive Statistics for the Live Streaming Sample (N = 834)

Variable	Follower-count category	Number of live streams
Streamer follower tier	Fewer than 100,000	14
	100,000–999,999	399
	1,000,000–9,999,999	386
	10,000,000 or more	35

A total of 834 live streams were selected from Huitun's real-time live streaming rankings. Huitun is a monitoring and analytics platform for Douyin live streaming. Under the classification criteria adopted in the Douyin live streaming e-commerce report, streamers with at least 10 million followers are classified as top-tier streamers. Those with between 1 million and 10 million followers are classified as upper-middle-tier streamers, those with between 100,000 and 1 million followers are classified as middle-tier streamers, and those with fewer than 100,000 followers are classified as long-tail streamers. Top-tier, upper-middle-tier, and middle-tier streamers collectively attract 98% of consumer participation (Huo et al., 2025). The sample is therefore highly representative of activity on the platform. All bullet-screen

data are collected between 7:00 p.m. and 10:00 p.m., when viewers are most active (Zeng et al., 2023). Using a consistent collection period reduces potential bias arising from differences in collection times. The consumer data are obtained from Huitun, including sales volume, viewer counts, and product information. The raw data are then cleaned and integrated. During data cleaning, system notifications indicating that users have entered the live streaming room and irrelevant comments containing emoticons, symbols, and hyperlinks are removed. The final dataset contains 1,487,082 valid bullet-screen comments. During data integration, the minute-level bullet-screen data are matched with the corresponding consumer data, resulting in 97,592 minute-by-minute real-time observations.

The keywords appearing in the bullet-screen comments are ranked by frequency in descending order. Table 2 reports the 30 most frequent keywords.

Table 2
Word-Frequency Statistics for Bullet-Screen Keywords (Top 30)

Keyword	Frequency	Keyword	Frequency	Keyword	Frequency
Top-left corner	195,002	Perks	62,362	Inventory	44,297
Huawei	101,298	Heart	56,450	Follow	44,281
Mobile phone	100,485	iPad	55,735	Get it first	43,406
Red packet	89,849	Mate60	54,869	Active	41,869
Lucky bag	86,172	Tablet	47,729	Pants	38,244
Make friends	85,242	Expedite	47,014	Keep it up	35,669
Finger heart	83,232	In stock	46,714	Facepalm	35,066
Apple	79,033	Celebrity's pick	46,164	Streamer	34,749
Link	78,345	Dear	44,828	Without hesitation	34,256
Shopping festivals	73,223	Payment	44,600	Gift bundle	34,131

The results indicate that bullet-screen comments contain both product-related information, including "Huawei," "mobile phone," and "Apple," and social information, including "make friends," "finger heart," and "heart."

4.2 Variable Definitions and Measurement

The effects of live-stream bullet-screen content on consumer behavior may change over time (Han et al., 2022; Zeng et al., 2023). To examine purchasing behavior at a finer temporal level, this paper uses minute-level product sales to measure consumers' actual purchasing behavior (Huo et al., 2025). This measure helps ensure the accuracy and objectivity of the findings. Because the Huitun platform collects sales data at shorter intervals as a live stream becomes more popular, the bullet-screen and sales data have to be aligned at the minute level. For each pair of adjacent

observation points, the difference in cumulative sales is divided by the length of the interval, and the resulting value is used as the sales volume for each intervening missing minute.

The independent variables consist of the content and behavioral characteristics of bullet-screen comments in live streaming e-commerce. The content characteristics comprise information richness, social interaction degree, and the sentiment polarity of bullet-screen comments. Information richness refers to the potential capacity of bullet-screen comments to convey product information (Han et al., 2022). To measure it, an e-commerce lexicon obtained from the Chinese Software Developer Network website is used to identify whether each bullet-screen comment contained product-related keywords. Information richness is then calculated as the proportion of comments containing product-related keywords in the total number of bullet-screen comments posted during each minute. The lexicon covers a broad range of product names and e-commerce-related keywords. Social interaction degree refers to the extent to which consumers engage in social interaction in a live streaming room to foster interpersonal relationships (Yang et al., 2023). It is measured using the Chinese social processes dictionary in Linguistic Inquiry and Word Count. Each bullet-screen comment is examined to determine whether it contained social-process keywords (Huo et al., 2025). Social interaction degree is then calculated as the proportion of comments containing such keywords in the total number of comments posted during each minute. The sentiment polarity of bullet-screen comments refers to the emotional attitudes toward live streaming content expressed by consumers through bullet-screen comments (Han et al., 2022). The sentiment score of each comment is identified using the sentiment analysis function of the natural language processing module on the Baidu Artificial Intelligence Open Platform. The mean sentiment score of the comments posted during each minute is then calculated as the measure of the sentiment polarity of bullet-screen comments. The behavioral characteristics of bullet-screen comments are represented by the number of bullet-screen comments. This variable refers to the number of comments posted by consumers in a live streaming room and is measured as the number of valid bullet-screen comments added per minute.

Streamer-product relevance serves as the moderating variable. It is obtained by manually coding the product-list data collected from Huitun. A value of 0 indicates low streamer-product relevance, referring to live streaming rooms that promote multiple product categories or brands. A value of 1 indicates high streamer-product relevance, referring to live streaming rooms that promote products from a single brand.

The analysis also controls for the number of tips, the number of likes, the number of viewers, and product price (Han et al., 2022; Zeng et al., 2023). The number of tips is measured as the number of tips received per minute. For missing intermediate time points, the number of likes is estimated by dividing the difference in cumulative likes between two adjacent observations by the length of the interval. The number of viewers is estimated using the mean of the values recorded at the two adjacent observation points. Product price is measured as the mean discounted post-coupon price of the products offered in each live stream (Zeng et al., 2023). Table 3 summarizes the measurement of all variables.

Table 3
Measurement of Variables

Variable type		Variable	Symbol	Description and measurement
Dependent variable		Purchasing behavior	*Purchase_Beh*	Increase in product sales per minute
Independent variable	Central route	Information richness	*Inf_Ric*	Proportion of bullet-screen comments containing product information in the total number of bullet-screen comments posted per minute
		Social interaction degree	*Soc_Int_Deg*	Proportion of bullet-screen comments containing social information in the total number of bullet-screen comments posted per minute
		Sentiment polarity of bullet-screen comments	*Sen_Bul_Scr*	Mean sentiment score of bullet-screen comments posted per minute
	Peripheral route	Number of bullet-screen comments	*Bul_Scr_num*	Number of bullet-screen comments added per minute
Moderating variable		Streamer-product relevance	*Bro_Pro_Rel*	0 = low streamer-product relevance; 1 = high streamer-product relevance
Control variable		Number of tips	*Gifts_num*	Number of tips received per minute
		Number of likes	*Likes_num*	Number of likes received per minute
		Number of viewers online	*Online_View_num*	Number of viewers online per minute
		Product price	*Com_Price*	Mean discounted product price in each live stream

4.3 Descriptive Statistics and Correlation Analysis

Table 4 presents the descriptive statistics for the variables. The skewness values of the number of bullet-screen comments, the number of tips, the number of likes, product price, and the number of viewers are all greater than 3. These variables are therefore natural-log-transformed. The correlation analysis shows that some correlation coefficients exceed 0.600. Variance inflation factors (VIFs) are consequently calculated to assess multicollinearity. All VIF values for the independent variables are below 10, indicating that multicollinearity is not a serious concern and that the hypothesized model is suitable for estimation. Table 5 reports the correlation analysis and multicollinearity diagnostics.

Table 4
Descriptive Statistics for the Variables

Variable	*M*	*SD*	*Min.*	*Max.*	Skewness
Purchase_Beh	19.366	159.882	0	20,305	57.095
Inf_Ric	0.509	0.388	0	1	–0.139
Soc_Int_Deg	0.763	0.399	0	1	–1.293
Sen_Bul_Scr	0.515	0.333	0	1	–0.393
Bul_Scr_num	15.116	104.118	0	23,122	137.651
Bro_Pro_Rel	0.768	0.422	0	1	–1.271
Gifts_num	2.724	74.832	0	22,430	277.783
Likes_num	449.071	2,879.383	0	158,384	20.155
Online_View_num	1,495.884	4,823.806	1	70,639	7.596
Com_Price	520.722	993.857	10.78	10,221.870	3.412

5 Empirical Analysis and Results

This paper employs a zero-inflated negative binomial regression model to test the research hypotheses. The model is selected for three reasons. Firstly, consumer purchasing behavior, the dependent variable, is a count rather than a continuous variable. With a skewness statistic of 57.095, the data exhibit a significant deviation from normality, which renders ordinary least squares regression inappropriate (Wu & Liu, 2017). A count regression model is therefore more appropriate. Secondly, the dependent variable has a mean of 19.366 and a variance of 23,562.253. The variance is substantially greater than the mean, violating the equidispersion assumption of the Poisson distribution and indicating overdispersion. A negative binomial regression model is therefore appropriate. Thirdly, zero observations account for 41.82% of the dependent variable. Moreover, the Vuong test produces a *Z*-statistic significantly greater than zero, indicating that the zero-inflated negative binomial model fits the data better than the standard negative binomial model. Table 6 presents the regression results.

5.1 Full-Sample Regression Results and Analysis

The full-sample model is estimated using zero-inflated negative binomial regression in Stata. Model 1 in Table 6 reports the results.

Among the content characteristics of bullet-screen comments, information richness (*Inf_Ric*) has a significant positive effect on consumer purchasing behavior, supporting *H1*. The greater the amount of product information conveyed by bullet-screen comments, the less uncertainty consumers perceive in making purchase decisions, which in turn promotes purchasing behavior (Hu et al., 2012). Social interaction degree (*Soc_Int_Deg*) also has a significant positive effect on consumer purchasing behavior, supporting *H2*. A greater amount

Table 5
Correlation Analysis and Multicollinearity Diagnostics

No.	Variable	1	2	3	4	5	6	7	8	9	10	VIF
1	*Purchase_Beh*	1										
2	*Inf_Ric*	0.034***	1									1.10
3	*Soc_Int_Deg*	0.042***	0.652***	1								1.12
4	*Sen_Bul_Scr*	0.038***	0.483***	0.666***	1							1.07
5	ln*(Bul_Scr_num)*	0.125***	0.032***	–0.140***	0.122***	1						1.52
6	ln*(Gifts_num)*	0.179***	0.100***	0.097***	0.125***	0.397***	1					1.36
7	ln*(Likes_num)*	0.152***	0.116***	0.153***	0.168***	0.381***	0.407***	1				1.81
8	*Bro_Pro_Rel*	–0.154***	–0.132***	–0.119***	–0.081***	–0.275***	–0.193***	–0.291***	1			1.31
9	ln*(Com_Price)*	–0.048***	0.099***	0.054***	0.065***	0.055***	0.096***	0.051***	0.083***	1		1.09
10	ln*(Online_View_num)*	0.187***	0.247***	0.311***	0.284***	0.618***	0.414***	0.607***	–0.503***	0.112***	1	2.33

***$p < 0.01$.

of social interaction-oriented content contributes to a more relaxed and pleasant live streaming atmosphere. Consumers consequently become more willing to participate in live streaming discussions and make purchases (Lin et al., 2021). The linear coefficient for the sentiment polarity of bullet-screen comments (*Sen_Bul_Scr*) is positive and significant, whereas its quadratic coefficient is negative and significant. According to Aiken and West (1991), this combination indicates that the positive effect of the independent variable diminishes as its value increases. The relationship between the sentiment polarity of bullet-screen comments and purchasing behavior is therefore inverted U-shaped, supporting *H3*. Positive sentiment expressed in bullet-screen comments initially promotes consumer purchasing behavior (Chevalier & Mayzlin, 2006). Once the level of positive sentiment becomes sufficiently high, however, consumers may begin to question the authenticity of the comments (Berger et al., 2010), which reduces purchasing behavior. Purchasing behavior is therefore lower at both the strongly negative and strongly positive ends of the sentiment spectrum.

Table 6
Regression Results

Variable	Model 1: Full sample	Model 2: High relevance	Model 3: Low relevance
Inf_Ric	0.226***	0.185**	0.194***
	(0.044)	(0.057)	(0.069)
Soc_Int_Deg	0.209**	0.125	0.277**
	(0.083)	(0.104)	(0.133)
Sen_Bul_Scr	1.220***	2.930***	1.199***
	(0.244)	(0.340)	(0.344)
$Sen_Bul_Scr^2$	–0.904***	–2.325***	–0.694**
	(0.205)	(0.279)	(0.296)
ln(*Bul_Scr_num*)	0.052***	0.025	0.060***
	(0.011)	(0.017)	(0.014)
ln(*Gifts_num*)	0.011	–0.075***	0.082***
	(0.015)	(0.021)	(0.020)
ln(*Likes_num*)	–0.056***	–0.085***	–0.014
	(0.008)	(0.011)	(0.012)
ln(*Online_View_num*)	0.942***	0.914***	0.778***
	(0.012)	(0.018)	(0.019)
ln(*Com_Price*)	–0.559***	–0.585***	–0.408***
	(0.010)	(0.014)	(0.015)
Constant	–1.396***	–1.459***	–1.066***
	(0.128)	(0.174)	(0.198)
ln(α)	1.068***	1.306***	0.830***
	(0.021)	(0.041)	(0.025)

(*To be continued*)

(*Continued*)

Variable	Model 1: Full sample	Model 2: High relevance	Model 3: Low relevance
log likelihood	–84,361.35	–41,961.63	–42,015.45
Prob > χ^2	0.000	0.000	0.000
Vuong test: ZINB vs. standard negative binomial	z = 13.01; Pr > z = 0.000	z = 8.37; Pr > z = 0.000	z = 11.59; Pr > z = 0.000

***$p < 0.01$, **$p < 0.05$.

The number of bullet-screen comments (*Bul_Scr_num*), which represents bullet-screen behavioral characteristics, has a significant positive effect on consumer purchasing behavior, supporting *H4*. A larger number of comments gives consumers a better understanding of the products offered in the live streaming room (Chevalier & Mayzlin, 2006). It also strengthens their perception of the presence of others and increases psychological arousal, thereby making them more willing to purchase the products (Zhou et al., 2019).

5.2 Grouped-Sample Regression Results and Analysis

The full-sample results show that both the content and behavioral characteristics of bullet-screen comments significantly affect consumer purchasing behavior. The analysis next examines whether streamer-product relevance moderates these relationships. The sample is divided into high- and low-relevance groups. Model 2 in Table 6 reports the results for the high-relevance group, and Model 3 reports those for the low-relevance group. A seemingly unrelated estimation test (SUEST) is conducted to determine whether the coefficients differed significantly between the two groups.

The between-group differences in the coefficients for information richness (0.009) and social interaction degree (0.152) are not significant. Streamer-product relevance, therefore, does not moderate the effects of information richness or social interaction degree on purchasing behavior. *H5a* and *H5b* are rejected. This result indicates that consumers pay attention to the information richness and social interaction degree of bullet-screen comments regardless of streamer-product relevance. Through these comments, they obtain additional product information and strengthen their relational bonds with streamers (Hu & Chaudhry, 2020; Zeng et al., 2023), thereby promoting purchasing behavior. The between-group differences in the linear coefficient (−1.730*) and quadratic coefficient (1.631**) for the sentiment polarity of bullet-screen comments are both significant. The positive effect of the sentiment polarity of bullet-screen comments on purchasing behavior extends over a wider range in live streaming rooms with high streamer-product relevance, supporting *H5c*. Consumers in these live streaming rooms are highly involved and devote greater cognitive effort to processing the content cues conveyed by bullet-screen comments. They are therefore

less likely to question the authenticity of the sentiment expressed in the comments.

For bullet-screen behavioral characteristics, the between-group difference in the coefficient for the number of bullet-screen comments (0.035) is not significant. Streamer-product relevance, therefore, does not moderate the relationship between the number of bullet-screen comments and purchasing behavior. *H5d* is rejected. This result indicates that the number of bullet-screen comments generates psychological arousal and promotes purchasing behavior in both high- and low-relevance live streaming rooms.

5.3 Robustness Tests

Several robustness tests are conducted to verify the reliability of the findings. First, following the three-step procedure proposed by Haans et al. (2016), the UTEST command is used to further test the inverted U-shaped relationship between the sentiment polarity of bullet-screen comments and purchasing behavior. The first step requires the coefficient of the linear term to be positive and the coefficient of the quadratic term to be negative, with both coefficients statistically significant. As reported above, the linear and quadratic coefficients for the sentiment polarity of bullet-screen comments satisfy these conditions. The second step requires the slopes at the lower and upper bounds of the data range to be sufficiently steep and to have opposite signs. At the lower bound, the slope is positive and significant (slope = 1.220, $p < 0.001$). At the upper bound, the slope is negative and significant (slope = −0.587, $p < 0.01$). The slopes at the two bounds therefore have significantly opposite signs. The third step requires the turning point of the inverted U-shaped curve to fall within the observed data range. As shown in Table 7, the turning point is 0.675 and lies within the sample interval of 0 to 1. These results provide further support for the inverted U-shaped relationship between the sentiment polarity of bullet-screen comments and purchasing behavior.

Table 7

Test of the Inverted U-Shaped Relationship

Parameter	*LL*	*UL*
Boundary value	0	1
Slope	1.220	–0.587
t-value	4.995	–3.205
p-value	0.000	0.001
Turning point	0.675	

Second, negative binomial regression is used as an alternative model specification. Negative binomial and zero-inflated regression models are often used as alternative specifications in robustness tests based on large-scale behavioral data (Huo et al., 2025). The results presented in Table 8 show that the signs and significance of the coefficients for the core variables in the full-sample model are consistent with the main regression results. The SUEST results also

produce the same conclusions regarding the significance of the between-group coefficient differences. The between-group differences in the linear and quadratic coefficients for the sentiment polarity of bullet-screen comments are −2.321** and 2.040***, respectively.

Table 8
Robustness Test Results

Variable	Robustness check 2: Negative binomial regression		
	Model 1: Full sample	Model 2: High relevance	Model 3: Low relevance
Inf_Ric	0.208***	0.177*	0.217**
	(0.080)	(0.092)	(0.109)
Soc_Int_Deg	0.199*	0.132	0.199
	(0.119)	(0.136)	(0.195)
Sen_Bul_Scr	1.189**	2.972***	0.651
	(0.583)	(0.503)	(0.776)
$Sen_Bul_Scr^2$	–0.939**	–2.371***	–0.331
	(0.448)	(0.404)	(0.627)
ln(*Bul_Scr_num*)	0.046**	0.020	0.064**
	(0.019)	(0.025)	(0.026)
ln(*Gifts_num*)	–0.011	–0.078**	0.046
	(0.023)	(0.034)	(0.030)
ln(*Likes_num*)	–0.059***	–0.084***	–0.024
	(0.014)	(0.018)	(0.020)
ln(*Online_View_num*)	0.949***	0.917***	0.789***
	(0.019)	(0.029)	(0.031)
ln(*Com_Price*)	–0.565***	–0.586***	–0.421***
	(0.023)	(0.021)	(0.040)
Constant	–1.496***	–1.532***	–1.010**
	(0.270)	(0.263)	(0.403)
ln(α)	1.482***	1.412***	1.508***
	(0.016)	(0.021)	(0.021)
Pseudo R^2	0.061	0.054	0.034
log likelihood	–84,523.217	–41,965.063	–42,284.394
Prob > χ^2	0.000	0.000	0.000
Wald $\chi^2(9)$	4,714.99	2,639.03	1,200.11

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

Finally, the hypotheses are retested after additional control variables are introduced. A streamer's number of followers reflects their popularity, while their product-selling reputation may affect consumers' trust in and attitudes toward them and consequently influence purchasing behavior (Huo et al., 2025). The streamer's number of followers and product-selling reputation are therefore added to the regression model as control variables. As shown

in Table 9, the signs and significance levels of the coefficients for the core variables in the full-sample model remain consistent with the main results. The SUEST results also remain consistent with the earlier findings. Specifically, the between-group differences in the linear and quadratic coefficients for the sentiment polarity of bullet-screen comments are −1.942** and 1.850**, respectively. These findings further confirm the robustness of the results.

Table 9

Robustness Test Results with Additional Control Variables

Variable	Robustness check 3: Additional control variables		
	Model 1: Full sample	Model 2: High relevance	Model 3: Low relevance
Inf_Ric	0.201***	0.122**	0.198***
	(0.044)	(0.056)	(0.069)
Soc_Int_Deg	0.223***	0.124	0.272**
	(0.082)	(0.102)	(0.134)
Sen_Bul_Scr	1.218***	3.128***	1.187***
	(0.244)	(0.335)	(0.345)
Sen_Bul_Scr^2	–0.902***	–2.530***	–0.679**
	(0.205)	(0.276)	(0.298)
ln(*Bul_Scr_num*)	0.052***	0.013	0.059***
	(0.011)	(0.017)	(0.015)
ln(*Gifts_num*)	0.023	–0.084***	0.078***
	(0.015)	(0.021)	(0.021)
ln(*Likes_num*)	–0.051***	–0.079***	–0.016
	(0.008)	(0.011)	(0.013)
ln(*Online_View_num*)	0.944***	0.915***	0.777***
	(0.012)	(0.018)	(0.019)
ln(*Com_Price*)	–0.563***	–0.613***	–0.411***
	(0.010)	(0.013)	(0.015)
ln(*Follower*)	–0.039***	–0.175***	0.010
	(0.010)	(0.016)	(0.014)
WordofMouth	0.062	0.524***	0.036
	(0.056)	(0.100)	(0.071)
Constant	–1.504***	–1.325**	–1.333***
	(0.049)	(0.602)	(0.380)
ln(α)	1.063***	1.196***	0.831***
	(0.021)	(0.038)	(0.025)
log likelihood	–84,353.05	–41,878.53	–42,015.02
Prob > χ^2	0.000	0.000	0.000
Vuong test: ZINB vs. standard negative binomial	z = 12.95; Pr > z = 0.000	z = 9.39; Pr > z = 0.000	z = 11.39; Pr > z = 0.000

***$p < 0.01$, **$p < 0.05$.

6 Research Contributions and Future Directions

6.1 Research Contributions

Based on the ELM, this paper develops a model of the factors influencing consumer purchasing behavior in live streaming e-commerce. It examines the content characteristics of bullet-screen comments as central-route cues and their behavioral characteristics as peripheral-route cues, while also considering the moderating role of streamer-product relevance. This paper makes several theoretical and practical contributions.

The major theoretical contributions are as follows. Firstly, this paper combines the distinctive features of bullet-screen comments in live streaming e-commerce with an established framework for classifying semantic content. It characterizes bullet-screen content in terms of information richness, the sentiment polarity of bullet-screen comments, and social interaction degree, thereby extending the literature on user-generated content. Secondly, drawing on the ELM, this paper develops a model of consumer purchasing behavior that incorporates both the content and behavioral characteristics of bullet-screen comments. This approach provides a more comprehensive account of the key factors influencing consumer purchasing behavior through bullet-screen comments. It also broadens the application of the ELM in live streaming e-commerce research. Thirdly, this paper analyzes minute-level bullet-screen and consumer data from 834 live streams. It therefore provides large-sample empirical evidence on how the content and behavioral characteristics of bullet-screen comments affect consumer purchasing behavior in live streaming e-commerce.

The findings also have practical implications. Live streaming e-commerce platforms should recognize the importance of bullet-screen comments to marketing effectiveness and encourage consumers to post them. Platforms can increase consumer engagement by organizing prize draws, establishing rankings, introducing point-based systems, and adding special visual effects to bullet-screen comments. Streamers should ensure that their spoken content and posted bullet-screen comments include both product information and social interaction-oriented information. They should also manage the interactive atmosphere to maintain a relatively stable level of sentiment polarity among consumers throughout the live stream. In addition, marketing strategies should be adjusted according to streamer-product relevance. When streamer-product relevance is high, for example, streamers can guide consumers and appropriately foster a more enthusiastic atmosphere in the live streaming room.

6.2 Research Limitations and Future Directions

Despite its rigorous empirical design and use of bullet-screen and related data, this paper has several limitations. Firstly, the data are obtained from Douyin alone. Future studies could compare data from multiple live streaming e-commerce platforms to strengthen the external validity of the findings. Secondly, because of data limitations, this paper does not examine how differences among consumer types affect purchase decisions. Future research could combine multiple methods to investigate whether consumer type moderates the effects of

bullet-screen comments on consumer purchasing behavior in live streaming e-commerce. Thirdly, this paper considers only the direct effects of bullet-screen comments on consumer purchasing behavior. The content and behavioral characteristics of bullet-screen comments may affect purchasing behavior through different mechanisms. Future research could therefore examine the underlying mechanisms through which these characteristics influence consumer purchasing behavior in live streaming e-commerce.

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