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Unveiling the influence of streamer characteristics on sales performance in live streaming commerce

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ABSTRACT

It is known that streamers play a special role in live streaming commerce, but there is a huge discrepancy in sales performance resulting from different characteristics of streamers. This study applies social influence theory to systematically analyze how streamer characteristics interact to affect sales performance. Using a unique dataset of 120,794 live streaming records from 597 streamers on Douyin platform, we establish a fixed effects model with unbalanced panel data. The results show that previous sales have strong momentum effects. Total views, number of live commercial products and live streaming duration all have a positive impact on sales volumes. Heterogeneity analysis reveals significant differences across identity types, industry types, and authentication statuses, with celebrities, streamers from entertainment and leisure sectors, and unverified streamers showing notably stronger gains. These findings provide empirical evidence to guide streamers and platforms in optimizing marketing strategies in the competitive live streaming commerce.

1. Introduction

Live streaming commerce combines live streaming and e-commerce, which is driven by streamers who promote products on streaming platforms (Ma et al., 2022). A research report indicates that the number of live streaming commerce users in China reached 833 million by December 2024 (CNNIC, 2025). To facilitate viewers directly participate in live streaming commerce, Douyin, Instagram, Taobao and other e-commerce platforms have launched live streaming commerce channels (Vaterlaus & Winter, 2021; Chen et al., 2022). As an emerging e-commerce paradigm, numerous companies adopt live streaming commerce to increase their product sales (Zheng et al., 2023). Different from traditional e-commerce, streamers play a crucial role in live streaming commerce because they constitute the primary driving force behind marketing activities (Li et al., 2024). In this regard, both practitioners and researchers alike have strong interests to understand how streamer characteristics influence sales performance in live streaming commerce.

The unique characteristics of streamers are directly linked to the core objectives of engaging consumers and influencing viewers' purchasing decisions (Hou et al., 2020). For example, as a top streamer on Taobao, Li Jiaqi achieved sales exceeding 3.2 billion RMB during China's "Double Eleven" shopping event in 2020 (Peng et al., 2021), demonstrating that streamers' influence is a key factor affecting sales performance. While previous studies have touched on streamer characteristics, there remains a noticeable gap in how these characteristics are classified and how they influence sales performance (Zhang et al., 2024). Existing classifications often appear fragmented and lack a strong theoretical basis, which makes it challenging to analyze roles of streamer characteristics in boosting sales in a systematic way. Additionally, much of the current research leans heavily on surveys, interviews or questionnaires (Lu & Chen, 2021; Chen et al., 2022; Yang et al., 2023a), which might not accurately reflect streamers' actual sales capabilities. Building on these gaps, this study seeks to address two key research questions: (1) What are the factors of social influence of streamer characteristics in live streaming commerce? (2) What is the mechanism of social influence of streamer characteristics affecting sales performance?

To address the above research questions, this study adopts social influence theory, which provides a well-established framework for understanding how individuals are influenced by others in decision-making processes. We classify streamer characteristics from two perspectives: informational social influence and normative social influence. The conceptual model is examined by a unique dataset from Douyin,

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known as TikTok abroad, which is the most popular short video and live streaming platform in China (Zhang, 2021). Empirically, we employ fixed effects model of unbalanced panel data for parameter estimation. The results show that previous sales, total views, number of live commercial products, and live streaming duration, as informational social influence factors, have a positive impact on sales performance. Additionally, significant heterogeneities exist in these factors across various aspects of normative social influence, such as identity types, industry types and authentication statuses. Our research thoroughly demonstrates the impact of different streamers characteristics on sales performance, providing profound insights for e-commerce platforms and streamers to formulate effective marketing strategies.

Our work has made several significant contributions. First, our study enriches the literature on online consumer behavior by utilizing the actual transaction data to investigate the relationship between streamer characteristics and purchase behavior in live streaming commerce. Previous studies primarily relied on interviews, surveys or questionnaires for data collection (Hou et al., 2020; Zhu et al., 2021; Li et al., 2024), and took "purchase intention" as consumers' purchase behavior (Sun et al., 2019; Zeng et al., 2022a). In this study, a panel data model is constructed utilizing 120,794 live streaming records, with sales volume as the indicator of streamer sales performance. The unique dataset provides a solid foundation for revealing the critical role of streamer characteristics in live streaming commerce. Second, our study deepens the understanding of how streamer characteristics influence sales performance, uncovering some streamer characteristics such as identity types, industry types, and authentication statuses, which have been less explored in previous research. Finally, this research extends the application of social influence theory in live streaming commerce and proposes a classification framework for streamer characteristics based on informational and normative social influences. It provides a new theoretical support for understanding how informational and normative social influence factors of streamers affect sales performance.

The remainder of this paper is structured as follows. Section 2 reviews the literature of streamer characteristics in live streaming commerce and research theory. Section 3 develops the research hypotheses. The data and variables will be introduced in Section 4. Section 5 outlines the establishment of econometric model and presents the empirical results to reveal how streamer characteristics affect sales performance. Finally, the concluding section will outline the key findings and broader implications in Section 6.

2. Literature review

2.1. Live streaming commerce

Live streaming is a method of real-time online transmission of media content, typically involving video and audio (Chen & Lin, 2018). Live streaming commerce, a fusion of live streaming and e-commerce, is typically conducted by presenters, web celebrities or opinion leaders who showcase a variety of goods or services through live streaming platforms and generate revenue in this process (Yang et al., 2023a).

Streamers act as information providers. Their characteristics—such as trustworthiness, credibility, and social presence—are widely recognized as crucial drivers of consumer purchase intentions (Sun et al., 2019; Meng et al., 2021; Zhang et al., 2022a). Moreover, interactions between consumers and streamers tend to be more effective than those among consumers alone, largely because deep engagement is often built on a foundation of trust in the streamers (Luo et al., 2024). When viewers feel a strong sense of social presence, it shortens the psychological distance, enhancing consumer engagement and encouraging purchases (Ma et al., 2022).

Despite much progress in the study of live streaming commerce, there are still a lot of gaps that need further investigation. One major problem is the lack of a coherent framework to classify the characteristics of streamers. Many studies tend to examine specific characteristics in isolation, without considering how these characteristics interact to affect sales performance. Another limitation is the frequent reliance on surveys and interviews due to lack of transaction data (Zhang et al., 2022a; Li et al., 2024). To fill these gaps, this paper aims to establish a systematic classification of streamer characteristics and integrate real transaction data to provide a clearer and more reliable theoretical framework for how these characteristics affect sales performance.

2.2. Streamer characteristics and sales performance

Research shows that streamer characteristics can directly affect consumer behavior and purchase intention (Sun et al., 2019). For example, Zhu et al. (2021) found that the physical attractiveness, professional knowledge and social appeal of streamers will not only shape consumers' perception, but also subtly guide them to make purchasing decisions. Sokolova & Kefi (2020) argued that the professionalism and consistency of streamers lead viewers to develop emotional identification, which ultimately results in purchasing decisions. Despite the importance of these characteristics, existing research lacks a unified framework for categorizing these characteristics.

To our knowledge, most studies on streamer characteristics are intuitive and do not analyze the types of influences these characteristics exert. Furthermore, most research employs surveys or interviews to explore how streamers affect user experience, decisions, and behaviors (Lu & Chen, 2021; Chen et al., 2022; Yang et al., 2023a), lacking empirical evidence from real transaction data. To illustrate how our study fits into the broader research context, we provide a comparison of previous studies on streamer characteristics in Table 1. We find that there is still no comprehensive framework for classifying streamer characteristics and systematically unveiling their influence on sales performance.

To address this gap, this study applies social influence theory as the guiding framework. We explore how streamer characteristics influence sales performance through the perspectives of informational social influence and normative social influences. This theoretical approach not only helps classify the different types of streamer characteristics but also provides deeper insights into how these characteristics drive consumer behavior and, consequently, impact sales outcomes.

2.3. Social influence theory and research model development

Social influence arises from interpersonal interactions, shaping individual behaviors and attitudes through the actions and opinions of others (Kuan et al., 2014). Social influence theory, first proposed by Deutsch & Gerard (1955), explains how social influences develop and are enacted through interactions. The theory distinguishes between two primary forms of social influence: informational and normative social influences. Informational social influence occurs when individuals accept others' information as a reflection of reality (Kuan et al., 2014). In contrast, normative social influence involves conforming to social norms, expectations, or authority figures to achieve acceptance and a sense of belonging (Ru et al., 2018). These two forms of social influences operate through distinct mechanisms and vary depending on varying contexts (Jia et al., 2023).

This study applies social influence theory to develop a systematic classification of streamer characteristics, dividing them into informational and normative social influence categories. The classification is particularly valuable as it differentiates between characteristics that drive consumer behavior through the provision of objective information and those that influence purchasing decisions by leveraging social norms, identification, or perceived authority (Hu et al., 2019; Fu et al., 2020).

In live streaming commerce, informational social influence of streamer characteristics plays a critical role in building consumer trust and guiding purchasing decisions. Unlike traditional e-commerce, where consumers primarily rely on static product descriptions and

Table 1
Literature review on streamer characteristics in live streaming commerce.

Sources	Characteristics	Methods	Theory	Research aims
Hou et al. (2020)	Sex；Humor appeals；Social status；Interactivity	Survey	Uses & gratification theory	Investigate what factors can affect people's continuous watching and consumption intentions.
Zhu et al. (2021)	Physical attractiveness；Social attractiveness；Professional ability	Survey	Cognitive-affective system theory	Explore how streamer characteristics influence consumer interaction propensity.
Zhao et al. (2021)	Personality；Professionalism；Streaming affordance	Regression analysis	Theory of affordance	Explore factors associated with streamers' popularity.
Zhang et al. (2022)	Expertise；Opinion leader, etc.	Interview	Grounded theory	Emphasize the importance of streamer characteristics.
Yang et al. (2023)	Gender；Assortment depth	Regression analysis	Signaling theory	Investigate the effect of streamer characteristics on sales volume.
Chen & Wu (2024)	Attraction；Social orientation, etc.	Questionnaire	Attachment theory	Unveil mechanisms that drive viewer' purchase intention.
Zhang et al. (2024)	Number of products；Average stay time	Regression analysis	Information overload theory	Identify factors that may exhibit curvilinear effects.
Li et al. (2024)	Similarity；Attractiveness；Popularity	Survey	ABC theory	Discuss how characteristics of streamers influence consumers' impulse consumptions.
This study	Previous sales; Total views；Number of live commercial products,Duration；Identity；Profession；Authentication	Regression analysis	Social influence theory	The theoretical framework provides the basis for the classification of streamer characteristics; we further explore the impact of streamer characteristics on sales.

reviews, live streaming offers a dynamic, real-time interaction that positions streamers as key sources of product information (Chen & Lin, 2018). Consumers rely on streamers to showcase product features, make comparisons with alternatives, and address any uncertainties, which helps reduce information asymmetry and improves decision-making efficiency (Yu et al., 2023). For example, a higher number of viewers and active engagement in live sessions signal attractiveness, making consumers more receptive to the information being presented (Lyu et al., 2022). Through detailed product demonstrations and real-time explanations, streamers provide information that helps viewers process complex product details efficiently (Sokolova & Kefi, 2020). It is valuable that streamers highlight the most relevant product information and mitigate information overload (Zhang et al., 2024).

On the other side, normative social influence of streamer' characteristics significantly also impacts consumer decision-making by fostering social conformity, identification, and community belonging. When consumers repeatedly encounter products recommended by streamers, their perception of these products often shifts from individual preferences to broader social norms, encouraging collective purchasing behavior (López et al., 2022). For example, the identity and status of a streamer—such as being a celebrity, a professional expert, or an ordinary individual—profoundly influence how their recommendations are received (Ru et al., 2018). Moreover, customers may be more inclined to choose accredited streamers, as their perceived professionalism and credibility enhance consumer trust (Jiang et al., 2025). As a result, the normative pressure drives consumers to make purchasing decisions

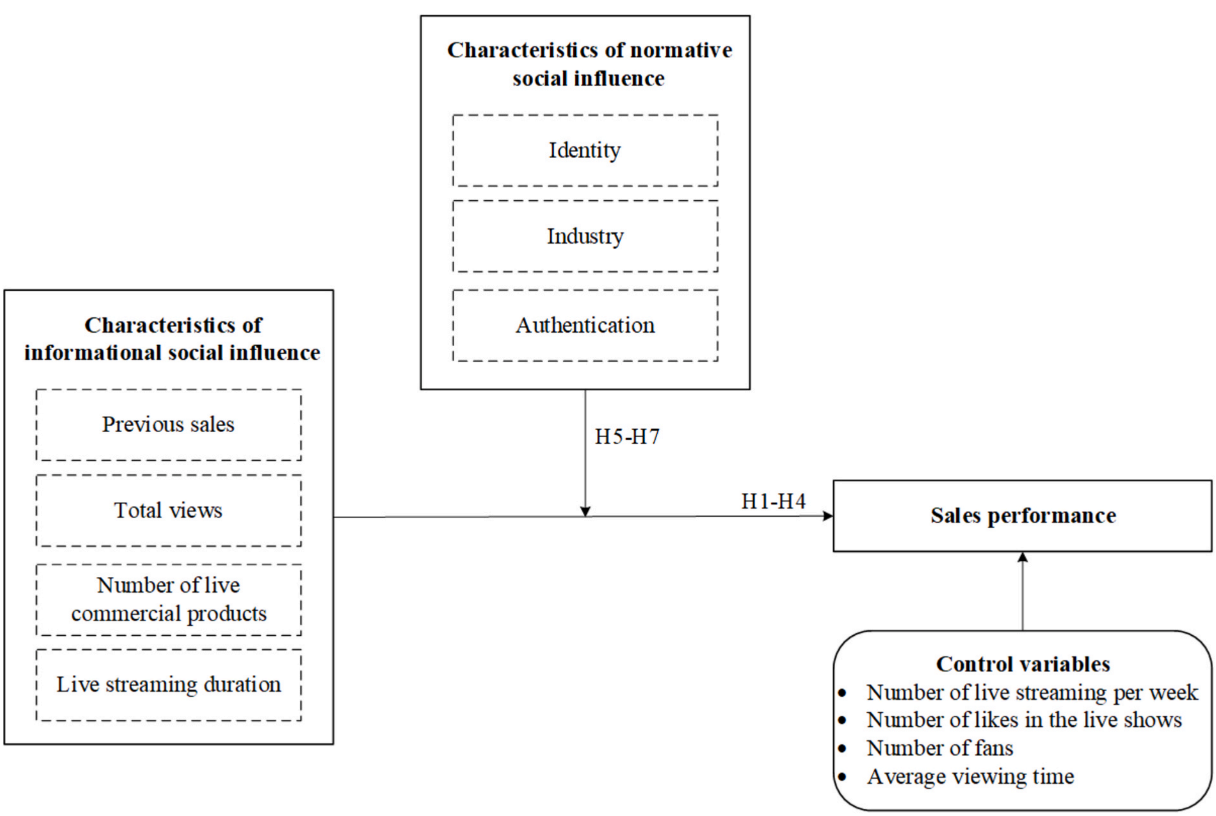

Fig. 1. The conceptual model.

influenced by the sense of belonging, identity, and social norms.

As illustrated in Fig. 1, guided by social influence theory, this paper seeks to systematically examine streamer characteristics on sales performance from the perspectives of information and normative social influence.

3. Hypotheses development

In this section, we will develop hypotheses on several potential factors influencing sales performance in live streaming commerce, drawing on social influence theory. Specifically, we propose 4 factors related to informational social influences and 3 factors associated with normative social influences. It is undoubtedly that streamer informational and normative influences encompass a broader range of factors. However, our study focuses on these key factors to unveil their influence mechanism. By narrowing the scope, we aim to maintain theoretical clarity and avoid potential confusion that could arise from an overly broad analysis.

3.1. Informational social influences

3.1.1. Previous sales

Social influence theory suggests that individual behavior are not only guided by direct information but also significantly influenced by observing others' behaviors and experiences (Jia et al., 2023). In live streaming commerce, a streamer's past sales performance acts as a powerful informational social influence. When consumers are confronted with numerous choices, they often look to a streamer's sales history as an indicator of both the credibility and reliability of promoted products. A strong sales record can function as a trust signal, enabling consumers to feel confident to make purchasing decisions efficiently (Xu et al., 2024).

Furthermore, previous sales performance, as an informational social influence factor, also effectively reduces information asymmetry (Yu et al., 2023). Streamers with strong sales histories often leverage their established trust and reputation to attract viewers, making their product recommendations more persuasive and easier for consumers to accept (Liao et al., 2023). This influence mechanism enables consumers make quicker decisions in live streaming. Therefore, we propose the following hypothesis:

H1: The previous sales performance of streamers positively influences their current sales performance.

3.1.2. Total views

In live streaming commerce, total views serve as a critical indicator of streamer attractiveness (Hu et al., 2017). From an informational social influence perspective, a high view count is a heuristic cue, suggesting the popularity and appeal of the live show. When faced with complex or ambiguous product information, consumers often turn to social cues like view counts to reduce uncertainty and guide their purchase decisions (Lu & Chen, 2021). A higher number of views not only indicates broader consumer engagement but also fosters increased participation during the live show (Hu et al., 2017). This increased involvement enhances informational social influence, as streamers can interact with more audience and provide detailed product information, all of which contribute to more informed consumers' purchasing decisions (Giertz et al., 2022). Based on this analysis, we propose the following hypothesis:

H2: Total views in live streaming have a positive impact on sales performance.

3.1.3. Number of live commercial products

The products sold in live streaming are referred to as live commercial products (Luo et al., 2021), which also acts as another informational social influence factor. The quantity of live commercial products presented directly affects the breadth of product information available to the consumers (Xin et al., 2024). A higher number of products showcased in a live streaming show enhances information availability, allowing consumers to compare options, assess features, and make more effective purchasing decisions (Xue et al., 2020). By presenting a wider selection, streamers can reduce information asymmetry and enhance consumer confidence in their choices. Additionally, product diversity enriches the live streaming content and promotes active engagement by appealing to a broad range of consumer interests and preferences (Andrews, 2016). Therefore, we propose the following hypothesis:

H3: The number of live commercial products has a positive impact on sales performance.

3.1.4. Live streaming duration

Live streaming duration refers to the total length of a live streaming session, which serves as another critical indicator of informational social influence. The duration of a live streaming affects how many products can be showcased, how thoroughly product demonstrations can be conducted, and how much interaction can occur between the streamer and the audience (Kang et al., 2021). Longer live streaming sessions provide streamers with more opportunities to highlight product features, offer comparisons with alternatives, and address audience questions in real-time (Wang & Li, 2020). This extended interaction helps reduce information asymmetry by delivering more comprehensive and transparent product information (Lu & Chen, 2021). Moreover, a prolonged streaming duration allows streamers to engage with a broader audience, creating deeper connections and a stronger sense of social presence, which can boost consumer trust and increase purchase intention (Chen et al., 2023). Based on this analysis, we propose the following hypothesis:

H4: Live streaming duration has a positive impact on sales performance.

3.2. Normative social influences

3.2.1. Identity types

Normative social influence suggests that individuals often align their decisions with social norms, expectations, or the perceived authority of others (Li, 2013; Hu et al., 2019). In live streaming commerce, a streamer's identity type is a key normative social influence factor, as it affects consumer trust, social identification, and purchase behavior beyond the objective information presented (Ogbanufe & Gerhart, 2022). Different identity categories of streamers—ordinary streamers, professionals and celebrities—convey unique social signals that shape how consumers influence their willingness to follow purchasing suggestions.

Ordinary streamers, who are not affiliated with major brands or media figures, attract audiences through authenticity, relatability, and peer-like interactions. Consumers may find them trustworthy because their product recommendations are seen as unbiased and grounded in genuine user experiences (Yang et al., 2023a). In contrast, professional streamers, such as industry experts, exert authority-based influence, as consumers perceive them as credible sources of expertise (Sokolova & Kefi, 2020). These professional streamers build trust through demonstrated knowledge and consistent messaging, contributing to higher sales performance. Celebrities, with their widespread public recognition, typically capitalize on their established fan base to drive consumer trust and engagement (Zhu et al., 2021). Their endorsements can generate a halo effect, prompting consumers to reinforce their purchasing decisions through desired recognition (Ma et al., 2022). Given the multiplicity and interactivity of streamer characteristics, we propose the following hypotheses:

H5a: There is heterogeneity in the impact of previous sales on sales performance across different streamer identity types.

H5b: There is heterogeneity in the impact of total views on sales performance across different streamer identity types.

H5c: There is heterogeneity in the impact of number of live commercial products on sales performance across different streamer identity types.

H5d: There is heterogeneity in the impact of live streaming duration on sales performance across different streamer identity types.

3.2.2. Industry types

In live streaming commerce, industry type also serves as a critical normative social influence factor.

The industry background of a streamer implicitly establishes expectations regarding their credibility, content, and audience base, thereby shaping the strength and nature of their normative influence (Sun & Bao, 2023).

For instance, streamers engaged in lifestyle and culture (LC) sector—such as wellness coaches, educators, or culinary experts—are often perceived as knowledgeable authorities in their respective fields (Zhang et al., 2023). Audiences expect professional insights, detailed product demonstrations, and expert recommendations (Jia et al., 2024), making endorsements of streamers more influential in guiding consumer purchases.

Conversely, entertainment and leisure (EL) streamers, such as gaming influencers, comedians, or travel vloggers, rely more on charisma, entertainment value, and social engagement rather than domain-specific expertise (Chen & Wu, 2024). While they can still exert normative influence, their recommendations may be perceived as more casual and experience-based. As a result, consumers may be more inclined to make impulse purchases driven by peer influence, social bonding, or parasocial relationships (Lo et al., 2022). Likewise, we propose the following hypotheses:

H6a: There is heterogeneity in the impact of previous sales on sales performance across different streamer industry types.

H6b: There is heterogeneity in the impact of total views on sales performance across different streamer industry types.

H6c: There is heterogeneity in the impact of number of live commercial products on sales performance across different streamer industry types.

H6d: There is heterogeneity in the impact of live streaming duration on sales performance across different streamer industry types.

3.2.3. Authentication statuses

Authentication statuses serve as another key aspect of normative social influences. On live streaming platforms like Douyin, streamers with verified statuses display authentication badges on their account homepages, such as singer, official store, enterprise, or internet celebrity (Jiang et al., 2025). By acting as institutional endorsements, such certifications communicate to consumers that the streamer meets the platform's credibility standards, thereby enhancing perceived legitimacy and reducing consumer skepticism. (Fu et al., 2024).

Obviously, verified streamers inherently possess a trust advantage, as their platform-endorsed status enhances their perceived authority and reliability (Zhang et al., 2021). This institutional validation makes their live streaming shows more attractive, as consumers are increasingly likely to accept their recommendations without extensive scrutiny. In contrast, unverified streamers lack this initial credibility buffer and must instead rely on consistent audience engagement, frequent product demonstrations, and interactive communication to establish credibility over time. Therefore, we propose the following hypotheses:

H7a: There is heterogeneity in the impact of previous sales on sales performance across different streamer authentication statuses.

H7b: There is heterogeneity in the impact of total views on sales performance across different streamer authentication statuses.

H7c: There is heterogeneity in the impact of number of live commercial products on sales performance across different streamer authentication statuses.

H7d: There is heterogeneity in the impact of live streaming duration on sales performance across different streamer authentication statuses.

4. Data

4.1. Data collection and preprocessing

Douyin is widely recognized as a leading social media platform in both China and around the world (Vaterlaus & Winter, 2021). In this study, we collect Douyin live streaming records from Inmyshow Digital Technology Group (https://www.inmyshow.com). The original data recorded from September 17, 2022 to July 10, 2023, involving 597 randomly selected streamers. To ensure data quality, we conduct data preprocessing on these records. To eliminate invalid instances, we calculate duration percentiles and used the interquartile range method (IQR) for filtering, setting the upper boundary to approximately 7.65 h and the lower boundary to 10 min. We also removed instances where sales volume was zero and addressed missing values with mean filling and deletion of duplicate data, resulting in 120,794 valid live streaming commerce records.

Given the unbalanced panel data, we need to transform the data time granularity. On the one hand, daily intervals often lack data for many streamers, impacting the reliability of the results; on the other hand, monthly intervals would diminish the differences and details among individual streamers. Therefore, we obtained 17,745 weekly data entries across 43 weeks from 597 streamers. The format of research context is shown in Fig. 2.

4.2. Variable description

4.2.1. Dependent and independent variables

This study uses sales volume as the dependent variable because it reflects a product's market acceptance and popularity, indicating its acceptance among consumers (Luo et al., 2021). Specifically, sales volume is measured as the weekly average number of products sold during live streaming sessions, providing a clear and quantifiable metric of consumer purchasing behavior over a consistent time frame, which enhances the reliability of sales performance analysis. High sales volume demonstrates that the product is widely accepted in the market (Yang et al., 2023b). Specifically, we focus on 4 independent variables: total views in live streaming, the number of live commercial products, and live streaming duration, which collectively represent the informational social influence factors in this study. The use of logarithmic transformation is common in econometric models, as it effectively mitigates heteroscedasticity (Zhou et al., 2023). The descriptions of the dependent and independent variables are shown in Table 2.

4.2.2. Control variables

To ensure reliability of results, it is necessary to consider control variables to prevent estimation bias. This study controls for factors such as the frequency of live streaming *NWLS*, audience engagement *logNL*, streamer influence base *logNF*, and viewer retention *logAVD*. A higher frequency of live streaming can increase exposure and audience engagement, potentially impacting sales outcomes (Chen et al., 2023). Likes serve as a proxy for audience engagement and content appeal, which could indirectly affect consumers' purchase decisions (Zeng et al., 2022a). A larger fan base typically indicates greater reach and influence, providing streamers with a broader potential customer pool (Lin et al., 2024). Longer viewing durations suggest higher content attractiveness and viewer retention (Chen & Liu, 2024), which may lead to improved sales performance.

4.2.3. Descriptive statistics

The dependent variable, sales volume (*logSV*), has a mean of 5.95 with a standard deviation of 1.69, ranging from 0.00 to 13.96. This indicates a considerable variation in weekly sales volume among streamers. Among the independent variables, previous sales (*L.logSV*) is captured through first-order lag term of dependent variable, while total views (*logTV*), has a mean of 10.14 and a similar standard deviation of

Fig. 2. A case about a live streaming commerce and user home page on Douyin.

Table 2
Variable description.

Type	Notation	Variables description
Dependent Variables		
Sales volume	*logSV*	The logarithm value of weekly average live sales volume for each streamer.
Independent Variables		
Previous sales	*L.logSV*	The logarithm value of firs-order lag term of weekly average live sales volume for each streamer.
Total views	*logTV*	The logarithm value of weekly average total live views for each streamer.
Number of live commercial products	*logNLCP*	The logarithm value of weekly average number of live commercial products for each streamer.
Live streaming duration	*logLSD*	The logarithm value of weekly average live streaming duration (hour) for each streamer.
Controlled Variables		
Number of weekly live streaming	*NWLS*	The average number of live streaming show per week for each streamer.
Number of likes	*logNL*	The logarithm value of weekly average number of likes for each streamer.
Number of fans	*logNF*	The logarithm value of weekly average number of fans for each streamer.
Average viewing duration	*logAVD*	The logarithm value of weekly audiences' average viewing duration (second) for each streamer.

1.69, suggesting a consistent level of exposure across streams. The number of live commercial products (*logNLCP*), averages at 3.13 with a standard deviation of 1.05, showing moderate variation in product offerings during live sessions. The live streaming duration (*logLSD*), measured in hours, has a mean of 0.80 and a standard deviation of 0.55, indicating some variability in the length of live streaming sessions. The significant differences in the magnitude of these variables underscore the necessity of log transformation. The log transformation is employed not only to address heteroscedasticity but also to standardize the scale of variables with varying magnitudes, enhancing model stability and interpretability (Zhou et al., 2023). The data distribution details for all variables are presented in Table 3, including the control variables. Finally, these variables exhibit low variance inflation factors (VIFs), all below 2, indicating a minimal risk of multicollinearity in the model.

We also conduct a correlation matrix analysis of the variables in Table 4. Overall, the correlation matrix meets the expected hypotheses, showing that variables related to informational and normative social influence generally align with expected impacts on sales performance. Additionally, the relatively low correlations between most independent variables suggest minimal multicollinearity concerns, enhancing the robustness of the subsequent regression analysis.

5. Empirical analysis and results

5.1. Measurement model

This study utilizes a fixed effects model with unbalanced panel data to examine how informational and normative social influence factors affect sales performance in live streaming commerce. Given the significant variability in streaming frequency among streamers, the data presents an unbalanced panel structure. The fixed effects model is well-suited to this context, as it effectively controls for unobserved individual-specific characteristics that remain constant over time but

Table 3
Summary statistics (N = 17,745).

Variables	Mean	Std.Dev	Min	Median	Max	VIFs
logSV	5.95	1.69	0.00	5.85	13.96	/
logTV	10.14	1.69	3.37	10.14	16.48	2.91
logNLCP	3.13	1.05	0.00	3.19	5.93	2.72
logLSD	0.80	0.55	−1.79	0.83	2.02	1.68
NWLS	6.83	5.74	1.00	6.00	68.00	1.59
logNL	9.81	2.08	−6.91	9.88	17.96	1.07
logNF	13.55	1.06	11.39	13.36	17.63	1.06
logAVD	4.46	0.65	−6.91	4.47	8.92	1.05

Table 4
Variables correlations.

	1	2	3	4	5	6	7	8
logSV	1							
logviews	0.692 ***	1						
logNLCP	0.303 ***	−0.062 ***	1					
logLSD	0.179 ***	0.084 ***	0.155 ***	1				
num_live_week	−0.036 ***	−0.102 ***	0.141 ***	−0.086 ***	1			
ln_m_Live_Likes	0.549 ***	0.729***	−0.006	0.047 ***	−0.116 ***	1		
ln_m_Fans	0.413 ***	0.577 ***	−0.122 ***	−0.052 ***	−0.087 ***	0.406 ***	1	
ln_viewing_time	0.286 ***	0.407 ***	0.009	−0.001	−0.075 ***	0.615 ***	0.107 ***	1

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (Notes: The marks in subsequent tables have similar meanings.).

differ between streamers, which enhances the reliability of results (Chen et al., 2023).

To validate the choice of the fixed effects model, a Hausman test was performed to compare it against the random effects model (Chen & Wu, 2025). The test produced a chi-squared statistic of 96.67 with a p value of 0.000, confirming the fixed effects model as the preferred option. The model is specified as follows:

$$logSV_{it} = \alpha_i + \beta X_{it} + \gamma CVs_{it} + \mu_t + \epsilon_{it} \tag{1}$$

Among them, $logSV_{it}$ is the dependent variable, α_i represent individual fixed effects, X_{it} is a vector of key independent variables and β represents the coefficients of these variables. CVs_{it} is a vector of control variables and γ denotes the coefficients of control variables. μ_t are time fixed effects and ϵ_{it} is the stochastic disturbance term. Furthermore, by applying cluster-robust standard errors at the streamers level in the following regression analysis, this study controls for correlations between a streamer's observations over time, enhancing the accuracy and reliability of statistical inferences (Abadie et al., 2023).

5.2. Regression results

5.2.1. Previous sales and heterogeneity analysis

The regression results shown in Table 5 demonstrate that previous sales (*L.logSV*) have a consistently positive and statistically significant impact on current sales performance across all models, supporting H1. In the full sample, column (1), the coefficient for previous sales is 0.415, significant at the 1 % level. This coefficient means that a 1 % increase in previous sales leads to a 0.415 % increase in current sales performance while keeping other variables constant. This finding highlights the strong momentum effect in live streaming commerce, where prior sales success can generate a virtuous cycle of increased visibility, enhanced consumer trust, and continued sales growth.

Heterogeneity analysis by streamer identity types, columns (2) to (4), reveals notable differences in how previous sales influence sales performance. The impact of previous sales is most pronounced among ordinary streamers (OS), with a coefficient of 0.432, followed by professional streamers (PS) (0.330) and celebrities (0.228), suggesting that ordinary streamers may benefit more from sales momentum. Additionally, the significant P-values from the bootstrap fisher permutation test the coefficient difference between groups, indicating that the impact of previous sales on sales performance differs significantly across streamer identity types. Specifically, the P-value of 0.026 between ordinary streamers and professional streamers, 0.000 between ordinary streamers and celebrities, and 0.089 between professional streamers and celebrities suggest varying degrees of dependence on previous sales momentum among these groups. These findings support H5a, demonstrating that streamer identity types moderate the effect of previous sales on current sales performance.

When examining the impact of previous sales across different industry types, columns (5) and (6), streamers from both life and culture (LC) and entertainment and leisure (EL) sectors demonstrate positive and significant effects, with coefficients of 0.429 and 0.406,

Table 5
Impact of previous sales on sales performance and heterogeneity analysis of streamers characteristics.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Identity types			Industry		Authentication	
	Full samples	OS	PS	Celebrities	LC	EL	Unverified	Verified
L.logSV	0.415 ***	0.432 ***	0.330 ***	0.228 ***	0.429 ***	0.406 ***	0.418 ***	0.403 ***
	(26.94)	(27.12)	(5.49)	(3.58)	(22.47)	(19.02)	(21.25)	(16.51)
Constant	−6.639 ***	−5.863 **	−20.654	−28.122 *	−14.653 ***	−1.192	−5.087	−11.131 ***
	(−2.63)	(−2.35)	(−1.03)	(−1.70)	(−6.13)	(−0.35)	(−1.45)	(−3.86)
CVs Controlled	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Streamers fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,114	13,504	974	636	5,433	9,681	9,320	5,794
Adjusted R^2	0.353	0.365	0.281	0.388	0.397	0.330	0.342	0.374
P-value	/	0.026 **	0.000 ***	0.089 *	0.329		0.494	

Notes: Robust t-statistics in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. The P-value of inter-group coefficient difference was calculated based on the Fisher combination test method of bootstrap and repeated sampling 1000 times. The P-value in column (2) represents the test results comparing ordinary streamers and professional streamers, column (3) shows the comparison between ordinary streamers and celebrities, and column (4) also reflects the comparison between ordinary streamers and celebrities. Subsequent tables have the same annotation pattern.

respectively. However, the P-value (0.329) indicates no statistically significant difference between these two industries. This suggests that the momentum effect of previous sales is relatively consistent across different industry categories, leading to the rejection of H6a.

For the authentication status analysis, columns (7) and (8), the coefficients for unverified and verified streamers are 0.418 and 0.403, respectively. The P-value (0.494) shows no significant difference between the two groups, suggesting that previous sales impact current sales performance similarly, regardless of whether the streamer is certified. This finding indicates that the certification status does not create a significant differential effect of previous sales on sales performance, thus H7a is not supported.

Overall, the results provide evidence for the positive impact of previous sales on sales performance in live streaming commerce, particularly highlighting the stronger momentum effects for ordinary streamers. The lack of significant heterogeneity across industry types and certification statuses implies that the momentum effect of previous sales is a broadly applicable phenomenon, underscoring the universal importance of sales consistency and sustained performance in this dynamic e-commerce environment.

5.2.2. *Total views and heterogeneity analysis*

As shown in Table 6, the regression results indicate that total views (*logTV*) have a consistently positive and statistically significant impact on sales performance across all models, supporting H2. In the full sample, column (9), the coefficient for total views is 0.841, significant at the 1 % level. It suggests that, on average, a 1 % increase in total views is associated with a 0.841 % increase in sales performance, holding other variables constant. This strong positive effect highlights the importance of attracting a larger audience in live streaming commerce, as higher viewership enhances product exposure, boosts consumer engagement, and increases the likelihood of purchases.

Columns (10) to (12) show the impact of total views on sales performance among different streamer identities. The coefficients are 0.819 for ordinary streamers, 0.934 for professional streamers, and 1.072 for celebrities. These results suggest that celebrities benefit the most from increased total views, potentially due to their higher conversion rates and brand influence. Furthermore, the coefficient difference between groups further highlights the significance of these differences. The P-value of 0.100 between ordinary streamers and professional streamers is marginally significant at the 10 % level, suggesting that the effect of total views on sales performance is not uniform between these two groups. The P-value of 0.015 between ordinary streamers and celebrities is significant at the 5 % level, demonstrating that celebrities are significantly more effective than ordinary streamers in translating increased viewership into sales performance. However, the P-value of 0.158 between professional streamers and celebrities is not significant, indicating no substantial difference in how these two types of streamers leverage total views for sales gains. This lack of significance may result from both professional streamers and celebrities possessing a strong professional image and stable fan base, leading to a more consistent sales performance regardless of fluctuations in total views. The results indicate significant heterogeneity in the impact of total views on sales performance across different streamer identities, particularly highlighting the distinct advantage of celebrities over ordinary streamers, thus supporting H5b.

Columns (13) and (14) present the impact of total views across life and culture and entertainment and leisure industries, with significant coefficients of 0.774 and 0.890, respectively. The P-value of 0.070 indicates a significant difference at the 10 % level between these two industry types. This result suggests that streamers from entertainment and leisure sectors achieve a greater sales performance boost from increased total views compared to the life and culture sectors. Therefore, H6b is supported, confirming that there is a statistically significant difference in how total views influence sales performance across different industries.

Columns (15) and (16) compare unverified and verified streamers. Both groups show positive and significant coefficients (0.805 and 0.890). The P-value of 0.080 is significant at the 10 % level, suggesting a difference in how verified and unverified streamers convert total views into sales performance. This finding indicates that verified streamers may leverage higher viewership more effectively due to increased credibility and trust. Consequently, H7b is supported, as the authentication status significantly affects the relationship between total views and sales performance.

In summary, the results show that total views positively impact sales performance and that this effect varies by streamer identity, industry type, and authentication status. Celebrities, the entertainment and leisure sectors, and verified streamers benefit the most from increased viewership, highlighting the strategic value of audience engagement in live streaming commerce.

5.2.3. *Number of live commercial products and heterogeneity analysis*

The illustrated results in Table 7 reveal the number of live commercial products (*logNLCP*) has a consistently positive and statistically significant impact on sales performance across all models, supporting H3. In the full sample, column (17), the coefficient for the number of live commercial products is 0.721, significant at the 1 % level. This indicates that a 1 % increase in the number of products showcased during a live streaming is associated with a 0.721 % increase in sales performance, holding other variables constant. From the perspective of informational social influence, showcasing a greater variety of products provides consumers with more options and richer product information, reducing uncertainty and facilitating better purchasing decisions.

Heterogeneity analysis by streamer identity types in columns (18) to (20) reveals that the impact of the number of live commercial products

Table 6
Impact of total views in live streaming on sales performance and heterogeneity analysis of streamers characteristics.

Variables	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Full samples	Identity types			Industry		Authentication	
		OS	PS	Celebrities	LC	EL	Unverified	Verified
logTV	0.841 ***	0.819 ***	0.934 ***	1.072 ***	0.774 ***	0.890 ***	0.805 ***	0.890 ***
	(27.14)	(24.96)	(9.33)	(13.96)	(14.44)	(25.55)	(18.90)	(20.97)
Constant	−3.720	−2.624	−13.301	−23.480 **	−15.978 ***	4.303	−0.818	−10.200 ***
	(−0.98)	(−0.66)	(−0.89)	(−2.10)	(−4.09)	(1.01)	(−0.15)	(−2.71)
CVs Controlled	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Streamers fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,744	15,685	1,205	854	6,375	11,369	10,790	6,954
Adjusted R^2	0.408	0.406	0.390	0.527	0.438	0.397	0.364	0.489
P-value	/	0.100 *	0.015 **	0.158	0.070 **		0.080 **	

Table 7
Impact of number of live commercial products on sales performance and heterogeneity analysis of streamers characteristics.

Variables	(17) Full samples	(18) Identity types OS	(19) PS	(20) Celebrities	(21) Industry LC	(22) EL	(23) Authentication Unverified	(24) Verified
logNLCP	0.721 ***	0.718 ***	0.677 ***	0.792 ***	0.611 ***	0.773 ***	0.777 ***	0.608 ***
	(22.66)	(20.94)	(5.97)	(9.27)	(11.54)	(19.55)	(20.48)	(10.90)
Constant	−16.380 ***	−14.629 ***	−41.353 **	−41.189 ***	−25.892 ***	−10.306 **	−14.667 ***	−21.880 ***
	(−5.12)	(−4.48)	(−2.21)	(−2.93)	(−6.72)	(−2.58)	(−3.44)	(−5.28)
CVs Controlled	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Streamers fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,744	15,685	1,205	854	6,375	11,369	10,790	6,954
Adjusted R^2	0.344	0.341	0.348	0.465	0.339	0.352	0.353	0.341
P-value	/	0.479	0.205	0.020 **	0.027 **		0.000 **	

varies among different types of streamers. The coefficients are 0.718 for ordinary streamers, 0.677 for professional streamers, and 0.792 for celebrities, suggesting that celebrities benefit the most from presenting a broader product selection. However, the P-values for the differences between groups show mixed results. The P-values of 0.479 (ordinary vs. professional streamers) and 0.205 (ordinary vs. celebrities) are not significant, indicating no substantial differences between these groups. Only the P-value of 0.020 between professional streamers and celebrities is significant at the 5 % level, highlighting that celebrities are more effective in leveraging product variety to boost sales performance. Therefore, H5c is only partially supported, showing limited heterogeneity by streamer identity.

The analysis of industry types, columns (21) and (22), shows that streamers from entertainment and leisure sectors (0.773) benefits more from a diverse product selection compared to the life and culture sectors (0.611), with a P-value of 0.027 indicating a significant difference at the 5 % level. This result supports H6c, demonstrating that the effectiveness of showcasing a larger number of products varies significantly between different industries.

Regarding authentication status, in columns (23) and (24), both unverified and verified streamers exhibit positive and significant coefficients (0.777 and 0.608), but the P-value indicates a highly significant difference at the 1 % level. Unverified streamers appear to gain more from offering a wide range of products, possibly because they rely on product variety to build trust and attract diverse audiences. This result supports H7c, confirming that the authentication status significantly affects the influence of the number of live commercial products on sales performance.

The results underscore the strategic importance of product variety in live streaming commerce, with significant differences observed across streamer identities, industry types, and authentication statuses.

5.2.4. Live streaming duration and heterogeneity analysis

The results in Table 8 also reveal that live streaming duration (*logLSD*) positively and significantly influences sales performance across all models, providing strong support for H4. In the full sample, the coefficient for live streaming duration is 1.073 in column (25), demonstrating significance at the 1 % level. This indicates that extending the live streaming duration by 1 % (in hours) is associated with an approximate 1.073 % increase in sales performance, holding all other variables constant. From the perspective of informational social influence, longer live streaming sessions allow streamers to provide more detailed product information, engage with audiences in-depth, and address viewer questions, which helps reduce consumer uncertainty and promotes purchase decisions.

Examining streamer identity types, in columns (26) to (28), the coefficients for ordinary streamers, professional streamers, and celebrities are 1.076, 1.060, and 1.100, respectively. These similar coefficients suggest that the effect of live streaming duration on sales performance is relatively consistent across different streamer identities. The P-values of 0.500, 0.444, and 0.387 indicate no significant differences among these groups, suggesting that extending live streaming duration is equally beneficial for all streamer types. Therefore, H5d is not supported, as there is no evident heterogeneity based on streamer identity.

For streamers from industry types, in columns (29) and (30), the coefficients are 0.956 for life and culture and 1.137 for entertainment and leisure. The P-value of 0.017 reveals a significant difference at the 5 % level, indicating that the entertainment and leisure sectors gain more from longer live streaming sessions. This may be due to the engaging and immersive nature of entertainment content, where prolonged interactions can enhance viewer engagement and increase the likelihood of purchases. These findings support H6d, showing that the impact of live streaming duration on sales performance varies significantly by

Table 8
Impact of number of live streaming duration on sales performance and heterogeneity analysis of streamers characteristics.

Variables	(25) Full samples	(26) Identity types OS	(27) PS	(28) Celebrities	(29) Industry LC	(30) EL	(31) Authentication Unverified	(32) Verified
logLSD	1.073 ***	1.076 ***	1.060 ***	1.100 ***	0.956 ***	1.137 ***	1.137 ***	0.988 ***
	(27.05)	(25.29)	(7.97)	(7.07)	(14.40)	(23.56)	(20.04)	(18.99)
Constant	−14.330 ***	−12.633 ***	−34.43 *	−40.396 ***	−25.251 ***	−6.969	−11.717 **	−21.106 ***
	(−4.25)	(−3.63)	(−1.70)	(−3.56)	(−6.76)	(−1.62)	(−2.44)	(−5.64)
CVs Controlled	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Streamer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,744	15,685	1,205	854	6,375	11,369	10,790	6,954
Adjusted R^2	0.325	0.328	0.296	0.420	0.342	0.319	0.311	0.360
P-value	/	0.500	0.444	0.387	0.017 **		0.015 **	

industry type.

The heterogeneity analysis by authentication status in columns (31) and (32) presents significant coefficients of 1.137 for unverified streamers and 0.988 for verified streamers at 1 % level, with a P-value of 0.015, significant at the 5 % level. The result suggests that unverified streamers benefit more from extending live streaming duration compared to verified streamers. This could be because unverified streamers rely on longer sessions to build trust and connect with audiences, compensating for the lack of formal verification. Consequently, H7d is supported, indicating a significant difference in the influence of live streaming duration on sales performance based on the streamer's authentication status.

In summary, the results demonstrate the significant positive impact of live streaming duration on sales performance. While the impact of live streaming duration remains consistent across different streamer identities, it varies significantly depending on industry types and authentication statuses.

5.3. Robust check

To enhance the robustness of the empirical results, this study applies the system generalized method of moments (SYS-GMM) approach. The SYS-GMM method offers distinct advantages for analyzing dynamic panel data by addressing potential endogeneity, controlling for unobserved individual effects, and reducing measurement errors (Khan et al., 2019).

The results of robustness tests are shown in Table 9, where the results in columns (33) to (40) are largely consistent with the findings from the fixed effects panel data models, confirming the reliability of the main empirical conclusions. Notably, *L.logSV* continues to show a positive and significant impact on current sales performance across all models, reaffirming H1. Similarly, the coefficients for *logNLCP* and *logLSD* remain positive and significant, providing strong support for hypotheses H3 and H4, respectively.

The heterogeneity analysis shows that the impact of these variables differs across streamer identities, industry types, and authentication statuses, reinforcing the findings from earlier results. For example, celebrities and verified streamers continue to show higher coefficients, indicating their stronger ability to translate sales momentum and product variety into improved sales performance. Similarly, the entertainment and leisure industries outperform the life and culture sectors, particularly benefiting from longer live streaming durations.

To verify the validity of the SYS-GMM model, several diagnostic tests are applied. The AR(1) test results indicate significant first-order autocorrelation ($p < 0.05$), while the AR(2) test results show no significant second-order autocorrelation ($p > 0.1$), validating the model's dynamic specification (Blundell & Bond, 1998; Jing et al., 2023). The Hansen test of overidentifying restrictions yields p-values above 0.1 across all models, indicating that the instrument set is valid and not overfitted. These diagnostic results strengthen the credibility of the SYS-GMM estimates and confirm the robustness of the empirical findings (Wu & Huang, 2022).

In conclusion, the SYS-GMM results corroborate the original fixed-effects model conclusions, demonstrating that the relationships between previous sales, live commercial products, and live streaming duration with sales performance are both statistically significant and economically meaningful. This robustness check ensures the empirical results are not sensitive to estimation methods, enhancing the overall reliability and validity of the study's findings.

6. Discussion and implications

6.1. Findings

Guided by social influence theory, this research systematically examines how factors such as previous sales, total views, number of live commercial products, and live streaming duration affect sales volume. The findings show that previous sales performance has a positive effect on current sales performance, supporting H1 and highlighting the momentum effect commonly seen in e-commerce, which is consistent with previous research finding (Yang et al., 2023b).

The analysis of total views demonstrates a significant positive effect on sales performance, supporting H2. The finding reinforces the idea that higher viewership not only enhances product visibility but also

Table 9
Results of robustness tests.

Variables	(33) Full samples	(34) Identity types OS	(35) PS	(36) Celebrities	(37) Industry LC	(38) EL	(39) Authentication Unverified	(40) Verified
L.logSV	0.155***	0.170***	0.126*	0.239	0.253***	0.180***	0.292***	0.172***
	(7.62)	(8.07)	(1.65)	(1.32)	(5.64)	(4.67)	(4.38)	(4.64)
logNLCP	0.783***	0.788***	0.655**	0.781***	0.832***	0.526***	0.624***	0.588***
	(8.86)	(8.76)	(2.39)	(2.58)	(6.56)	(6.74)	(5.27)	(7.00)
logNLCP	0.694***	0.752***	0.682**	0.435	0.747***	0.655***	0.684***	0.772***
	(7.38)	(7.23)	(2.33)	(1.00)	(5.75)	(8.12)	(4.48)	(8.63)
logLSD	0.261*	0.201	0.449	−0.097	0.010	0.480***	0.230	0.413***
	(1.95)	(1.55)	(1.28)	(−0.16)	(0.04)	(3.63)	(1.21)	(2.91)
Constant	−8.525***	−9.163***	−10.404*	55.289	−9.505***	−5.280***	−8.215***	−2.248
	(−4.44)	(−4.08)	(−1.67)	(0.53)	(−3.13)	(−3.69)	(−3.22)	(−1.39)
CVs Controlled	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Streamers fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,114	13,504	974	636	5,433	9,681	9,320	9,320
AR(1)	−11.01	−10.30	−3.033	−0.575	−6.191	−8.085	−6.864	−8.112
AR(1) p-value	0.000	0.000	0.002	0.565	0.000	0.000	0.000	0.000
AR(2)	0.531	0.603	−0.789	−0.415	0.462	1.244	1.608	0.634
AR(2) p-value	0.595	0.547	0.430	0.678	0.644	0.213	0.108	0.526
Hansen	424.1	442.3	37.27	8.886	150.1	335.8	182.8	295.5
Hansen p-value	0.421	0.645	0.111	0.782	0.981	0.140	0.470	0.118

Notes: Regression results are based on two-step SYS-GMM.

serves as social proof (Lu et al., 2021). We further identify significant heterogeneity, with celebrities, the entertainment and leisure industries, and verified streamers showing stronger responses to increased total views (H5b, H6b, and H7b supported). These results highlight how social cues, such as viewership numbers in live streaming session, contribute to encouraging purchasing decisions.

We confirm that a greater number of live commercial products positively impacts sales performance (H3 supported). From an informational social influence angle, offering a broader product selection provides consumers with richer information and more choices, which enhances their ability to make informed decisions (Xin et al., 2024). However, the heterogeneity analysis reveals that this effect varies significantly by industry type and authentication status (H6c and H7c supported), with entertainment and leisure sectors and unverified streamers benefiting more from a diverse product offering. The partial support for H5c suggests that while celebrities gain a marginal advantage from showcasing a wide range of products, the differences across streamer identities are not as pronounced.

Finally, the study also demonstrates that live streaming duration has a positive effect on sales performance (H4 supported). The heterogeneity analysis shows that the effect is more significant in the entertainment and leisure industries and among unverified streamers (H6d and H7d supported), suggesting that longer live streaming is particularly valuable in interactive and trust-building contexts (Kang et al., 2021). However, the absence of significant differences across streamer identities (H5d not supported) indicates that extending live streaming duration benefits all types of streamers relatively equally.

In conclusion, this study fills a critical research gap by applying social influence theory to live streaming commerce, systematically classifying informational and normative social influence factors of streamer characteristics. The findings not only enhance understanding of how these factors impact sales performance but also provide strong empirical evidence, validated through robust quantitative analysis.

7. Theoretical contributions

This study makes several key theoretical contributions. First, this study is one of the pioneer attempts to utilize the actual transaction data to investigate the relationship between streamer characteristics and purchase behavior in live streaming commerce. Previous related research primarily utilized interviews, surveys or questionnaires to investigate consumer behaviors, such as exploring user trust in streamers (Zhang et al., 2022b), interaction patterns between users (Zeng et al., 2022b), the convenience of streaming platforms (Xu et al., 2023), and interactions between consumers and streamers (Ye et al., 2022). In contrast, we employ sales volume as a direct indicator of sales performance, providing a more intuitive and direct insight to assess the impact of streamer characteristics on sales performance and purchase behavior. Thus, our research enhances the existing literature on online consumer behavior by unveiling how streamer characteristics can influence sales performance in live streaming commerce.

Second, we extend social influence theory by proposing a novel classification framework for streamer characteristics, categorizing these characteristics into informational and normative social influence factors. Although social influence theory has been widely applied in traditional e-commerce and social media contexts (Hollebeek et al., 2022; Gong et al., 2023), its application in live streaming commerce has been limited. This paper utilizes the theory to provide a theoretical foundation for categorizing streamer characteristics. Specifically, based on the framework of social influence theory, we offer a theoretical perspective to analyze how informational factors of streamers, such as previous sales, total views, number of live commercial products, and live streaming duration, help consumers reduce purchase uncertainty through information transmission (Xu et al., 2024), and how normative factors, such as identity types, industry types, and authentication statuses, shape consumer behavior through social norms (Ogbanufe & Gerhart, 2022).

Finally, our research develops an insightful model from a social influence perspective, enhancing the understanding of how streamer characteristics interactively affect sales performance in live streaming commerce. This model highlights the dual role of streamers as information providers and influencers of social norms (Gong et al., 2023), which enriches our knowledge of streamer characteristics in live streaming commerce. The heterogeneity analysis highlights significant variations when combining normative social influences with informational factors. For instance, the momentum effect of previous sales is more pronounced among ordinary streamers, while celebrities benefit more from increased total views. These interesting results offer valuable insights for streamers looking to optimize their sales performance and live streaming strategies.

8. Practical contributions

This study offers several practical contributions. On one hand, the findings underscore the importance of leveraging informational social influence factors, such as previous sales, total views, number of live commercial products, and live streaming duration, to boost sales performance. Streamers and marketers can strategically manage these factors by showcasing strong past sales, increasing viewer engagement, offering a diverse range of products, and extending live streaming sessions to enhance consumer trust and reduce purchase uncertainty (Zhang et al., 2024; Jiang et al., 2025).

On the other hand, this study provides new evidence that different streamer characteristics lead to significant differences in sales performance. Previous studies have considered the importance of streamers as influencers, such as key opinion leaders (KOLs), in consumers' purchasing decisions (Yang et al., 2023b). We further emphasizes the impact of different identity characteristics of streamers, ordinary streamers, professional streamers, and celebrities, on sales performance. For instance, we find that ordinary streamers exhibit a stronger momentum effect in previous sales. This stronger momentum effect can be attributed to ordinary streamers' greater potential for growth and proficiency in cultivating close connections with their audience, unlike professionals and celebrities, which boosts viewer engagement and loyalty (Zeng et al., 2022b). In addition to streamer identity types, we also examined the heterogeneity of industry types and certification statuses on sales performance. For example, celebrities and verified streamers benefit more significantly from increased total views and product variety and the streamers from entertainment and leisure industries outperform the life and culture sectors in maximizing sales through longer live streaming durations. Combined with the analysis of the three normative characteristics of identity types, industry types and authentication statuses, e-commerce platforms should formulate live streaming promotion strategies based on the actual situation of streamers (Gong et al., 2022), so as to amplify the advantages of different types of streamers (Chen et al., 2023).

8.1. Limitation and future research

While this study provides valuable insights into the impact of streamer characteristics on sales performance in live streaming commerce, it also has certain limitations that present opportunities for future research. First, one limitation is the study's focus on the immediate lagged effect to highlight the sales momentum, without fully exploring periodic trends that may occur within live streaming commerce. For example, seasonal promotions during major holidays such as Double 11, as well as seasonal product categories like fashion and perishable goods, could introduce cyclical influences on sales performance (Zhao, 2023). It is an opportunity for future research. Second, the study focuses on Douyin as the research platform. While different platforms have their unique user base and target audience (Wu et al., 2023), such as Taobao Live and Kuaishou, extending this research to other platforms would provide a broader understanding of the new marketing patterns in the live streaming commerce landscape. Third, while this study systematically analyzes streamer characteristics such as previous sales, identity types and so on, other potential informational and normative social influence factors remain underexplored. For instance, characteristics like interaction style (Zhou et al., 2019), charisma and social attractiveness might significantly influence sales performance (Lu & Chen, 2021). All the above are research directions we will focus on in the future.

CRediT authorship contribution statement

Xingpeng Xu: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Validation. **Qingfeng Zeng:** Writing – review & editing, Writing – original draft, Supervision, Software, Resources, Project administration, Investigation, Funding acquisition, Conceptualization. **Ri Na:** Resources, Project administration, Investigation, Data curation. **Weiguo Fan:** Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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