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Interactive Dynamics of Bullet Comments in Agricultural Livestreaming: A Dual-Path Analysis of Conversion Efficiency in Rural China

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Abstract

Live-streaming e-commerce is becoming a pivotal tool for promoting agricultural products and supporting rural revitalization in China. This study investigates the determinants of conversion efficiency-measured as Goods per Mille Views (GPM)-through a large-scale analysis of 70,650 agricultural livestream sessions on Douyin. Employing two-way fixed-effects panel regression and Bootstrap-based structural equation modeling (SEM), we examine how Retention Rate, Sales Amount, and Sales per Minute influence GPM. A key contribution of this study is the identification of a dual-path moderating effect of bullet comments (BulletCount), which can simultaneously enhance and hinder conversion depending on the context of viewer engagement. SEM results further uncover four significant mediation mechanisms-via Traffic Ratio, Retention Rate, Sales Amount, and Sales per Minute-through which bullet comments affect GPM. These findings offer new insights into the cognitive and social dynamics of interactive livestreaming. The study provides practical implications for platform designers, streamers, and policymakers seeking to improve conversion outcomes and foster sustainable rural e-commerce ecosystems.

Keywords: Live-streaming E-commerce; Conversion Efficiency; Bullet Comments; Rural Revitalization; User Engagement

1. Introduction

Digital infrastructure and mobile internet technologies drive market integration, reducing distribution bottlenecks in rural revitalization. In agriculture, this trend addresses longstanding challenges such as overstocked produce and limited market access faced by smallholder farmers, who often lack direct sales channels despite the expansive reach of large e-commerce platforms. Agriculture-themed livestreams enable rural producers, cooperatives, and local governments to bypass traditional intermediaries, connecting directly with consumers through real-time video commerce. This innovative model reduces distribution bottlenecks and enhances market integration, playing a crucial role in China's rural revitalization strategy that emphasizes modernization and digital transformation of rural industries.

Live-streaming e-commerce facilitates high-frequency interactions and lowers entry barriers while building consumer trust via authentic, place-based representations of agricultural production. However, although the macroeconomic benefits of rural live commerce are recognized, its micro-level conversion mechanisms remain underexplored. Viewer engagement metrics, particularly interactive features like bullet comments (BulletCount), have garnered interest but lack rigorous empirical assessment of their causal effects on conversion efficiency. Agricultural livestreaming uniquely combines severe information asymmetry, pronounced seasonality, and high trust requirements, complicating the purchase decision process. BulletCount may simultaneously act as social proof and urgency signal while imposing cognitive load or distracting viewers, leading to complex, potentially contradictory impacts on sales outcomes.

Understanding how interactive elements influence consumer behavior in this context is vital. Social proof theory suggests that visible interactions like BulletCount can enhance perceived product popularity and trust, boosting conversions. Conversely, cognitive load theory warns that excessive interaction may overwhelm viewers, reducing attention and impairing decision-making. Integrating these perspectives within a stimulus-organism-response (S-O-R) framework enables a holistic analysis of how BulletCount shapes buyer cognition and behavior in agricultural livestreams.

To fill this gap, this study proposes a comprehensive econometric framework integrating two-way fixed-effects panel regression and Bootstrap-based structural equation modeling (SEM). Using a dataset of 70,650 Douyin livestream sessions from 440 agricultural streamers, we investigate the direct, moderating, and mediating effects of BulletCount on Goods per Mille Views (GPM). Our results identify four significant indirect pathways, demonstrating BulletCount's dual role as both catalyst and constraint in the conversion funnel. This research contributes by deepening behavioral insights into interactive dynamics in live commerce, advancing theory through integration of social proof, cognitive load, and stimulus-organism-response (S-O-R) frameworks, and offering practical guidance for platform design and rural e-commerce development.

Furthermore, the findings hold implications beyond agriculture, shedding light on the broader role of real-time interaction in digital commerce ecosystems. By revealing how user-generated engagement can both enhance and inhibit conversion efficiency, this study informs platform moderators, content creators, and policymakers aiming to optimize interactive features for improved economic outcomes. Ultimately, the research supports the sustainable growth of digital rural markets by balancing technological innovation with user experience and trust-building strategies.

This paper proceeds in several integrated stages. Section 2 distils the interdisciplinary literature on rural revitalisation, live-stream conversion, and bullet-screen interaction into a three-pillar analytical framework centred on income dynamics, multidimensional deprivation, and policy interventions. Section 3 constructs a theoretically grounded research model that combines Social

Proof Theory, Cognitive Load Theory, and the Stimulus-Organism-Response (S-O-R) paradigm. Section 4 details the two-way fixed-effects panel regression and bootstrap-based SEM used to test hypotheses on 70,650 Douyin agricultural livestreams, after rigorous checks for reliability, validity, and endogeneity. Section 5 presents elasticity estimates of the drivers of GPM and formally examines the dual moderating and four-path mediating roles of bullet-comment density. Section 6 contrasts these findings with extant poverty and conversion studies, explicating how traffic, retention, sales volume, and sales velocity behave heterogeneously across high- and low-comment regimes. Section 7 and section 8 offer actionable prescriptions for optimising comment pacing, platform algorithms, and rural-streamer training, while outlining future research on cross-platform generalisability, qualitative comment semantics, and longitudinal experimentation.

2. Literature Review

2.1.Live-streaming E-commerce and Rural Revitalization

Live-streaming e-commerce has rapidly evolved from an entertainment-driven practice to a disruptive force in the digital economy. Zhang (2023) highlights how it blends real-time interaction with commercial transactions, while Guan et al. (2024) and Huang et al. (2025) emphasize its potential in dismantling traditional distribution barriers and connecting rural producers directly with urban consumers. In China, the alignment of livestreaming with agricultural product sales reflects broader national policies on “digitally enabled rural revitalization”.

Despite these advances, most prior research remains macro-level and descriptive. For instance, Tong et al. (2025) praise livestreaming for raising farmers’ marginal income, but they do not address the micro-level mechanisms that drive sales efficiency and conversion. Specifically, agricultural livestreaming introduces distinctive challenges absent from generic e-commerce: (1) Perishability, which heightens urgency and makes scarcity cues (“last 50 kg!”) more impactful; (2) Traceability, where viewers rely on live Q&A and social proof to assess authenticity; and (3) Trust deficits, where anchors’ rural identity and local reputation become decisive signals of credibility. These features indicate that agricultural livestreaming is not merely a subset of e-commerce, but a unique context where engagement mechanisms require re-examination.

This study builds on such insights by analyzing engagement-driven performance variables (e.g., bullet comments, retention, sales momentum) to move beyond descriptive accounts and provide an evidence-based micro-analytical framework.

2.2.Toward a Nuanced Understanding of Conversion in Livestreaming

Traditional e-commerce metrics such as Click-Through Rate (CTR) and Conversion Rate (CVR) inadequately capture livestreaming dynamics, as they overlook interaction intensity and real-time behavioral variance. Wang and Zhang (2024) propose GPM as a more holistic metric, integrating both traffic volume and monetization efficiency. This metric is particularly relevant for agricultural livestreams, which often operate in high-frequency, low-margin markets where efficiency per unit of exposure determines profitability.

However, the determinants of GPM remain under-theorized. Existing literature has not sufficiently examined how behavioral and psychological engagement variables-such as comment density, real-time scarcity cues, and cumulative trust signals-translate into commercial performance. This gap is particularly problematic in agriculture, where information asymmetry is more severe due to perishability and origin uncertainty.

To address this, the present study introduces a multi-path framework, arguing that GPM is shaped both directly (by traffic and sales) and indirectly (by interactive engagement dynamics). This perspective not only extends the understanding of livestream conversion but also aligns with the Stimulus-Organism-Response (S-O-R) model, which posits that environmental stimuli influence internal states, which in turn drive behavioral responses.

2.3.Bullet Comments: A Double-Edged Sword in Interactive Commerce

Bullet comments (BulletCount) have emerged as a defining feature of livestream commerce, transforming from a purely social entertainment tool into a critical trust-building and decision-shaping mechanism. Zeng et al. (2023) and Hsiao et al. (2023) demonstrate that high comment density fosters social proof and community belonging, which can enhance purchase intention. In agricultural livestreams, Zhang and Hu (2024) show that bullet comments enhance geographical traceability credibility, alleviating skepticism over origin and food safety.

Yet, bullet comments are not unambiguously beneficial. Zhang et al. (2023) and Jawad (2025) caution that excessive density can trigger cognitive overload, diverting attention from product details and undermining informed decision-making. This tension illustrates that bullet comments may act as both mediators and moderators: they can reinforce retention effects on GPM when used judiciously, but also suppress conversion when information congestion overwhelms consumers.

The dual role of bullet comments resonates with Cognitive Load Theory, which predicts performance deterioration under excessive stimuli, and Social Proof Theory, which explains how collective cues can enhance trust. Within the S-O-R framework, bullet comments operate as stimuli that can either enrich or overload the consumer's psychological processing, ultimately shaping purchase outcomes. By positioning BulletCount at the center of this theoretical intersection, this study advances a more nuanced account of how interactivity functions in agricultural livestream commerce (Figure 1).

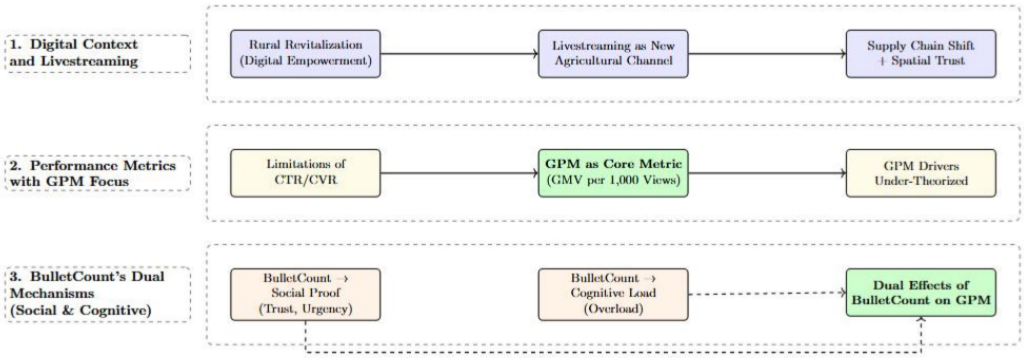

Figure 1. Conceptual Framework: From Digital Empowerment to GPM via Interactive Mechanisms

3. Research Model and Hypotheses Development

3.1. Theoretical Foundation

3.1.1. Social Proof Theory

Social Proof Theory posits that individuals rely on others' behaviors as heuristics for decision-making, particularly under uncertainty, as demonstrated by Do and Vo (2021). In agricultural livestreams—where product verification is difficult and trust deficits prevail—bullet comments operate as real-time social signals that shape perceived product quality, popularity, and seller credibility.

Positive comment density functions as a bandwagon cue, encouraging impulse purchases and reinforcing perceived authenticity, especially when users reference freshness, taste, or past satisfaction. Moreover, agriculture-specific cues—such as viewers vouching for a known farmer or locality ("this is from my hometown")—provide geographic social proof, which is especially influential in fostering trust in rural brands.Empirical studies suggest that such interactive endorsement mechanisms significantly elevate viewers' psychological safety and purchasing intention in livestream e-commerce.

3.1.2. Cognitive Load Theory

Mutlu-Bayraktar et al. (2019) found Cognitive Load Theory emphasized that human working memory had limited processing capacity, and excessive information can hinder comprehension and decision-making. Agricultural purchases require simultaneous evaluation of complex attributes (e.g., organic certification, price volatility), where information salience critically shapes decision quality.

High-density bullet comments may obscure essential product details, especially during in-depth product explanation segments. The resulting information overload elevates mental effort and reduces decision quality, particularly when time-sensitive decisions (e.g., "buy within 5 minutes to get free shipping") intersect with cognitively demanding content.

This overload effect is amplified in agricultural contexts due to the ephemeral nature of freshness and the need to assess multiple product dimensions simultaneously (e.g., origin, taste, logistics). Prior studies suggest that such overload leads to viewer fatigue, drop-off behavior, and ultimately lower conversion efficiency.

3.1.3. Stimulus–Organism–Response (S-O-R) Framework

The Stimulus-Organism-Response(S-O-R) framework provides an integrative model explaining how environmental stimuli trigger internal psychological states that shape behavioral outcomes. In livestream e-commerce, bullet comments act as dynamic external stimuli, influencing the viewer's internal state (organism) — such as urgency, reassurance, or confusion — which subsequently affects behavioral responses like retention or purchase.

For instance, scarcity-driven messages (e.g., “Only 10 boxes left!”) may evoke urgency and shorten the decision cycle, increasing GPM. In contrast, Hochreiter et al. (2022) found a flood of irrelevant or fragmented comments could increase cognitive tension or reduce emotional engagement, leading to premature exit behavior or disengagement from the purchase process.

This framework helps reconcile the contradictory roles of bullet comments: they can both activate emotional triggers that boost conversion and introduce cognitive strain that suppresses it. The S-O-R model thus accommodates the dual-channel mechanism of interactive elements in shaping monetization outcomes within high-engagement, high-stakes environments like agricultural livestreams. This logic is illustrated in the conceptual framework (Figure 2).

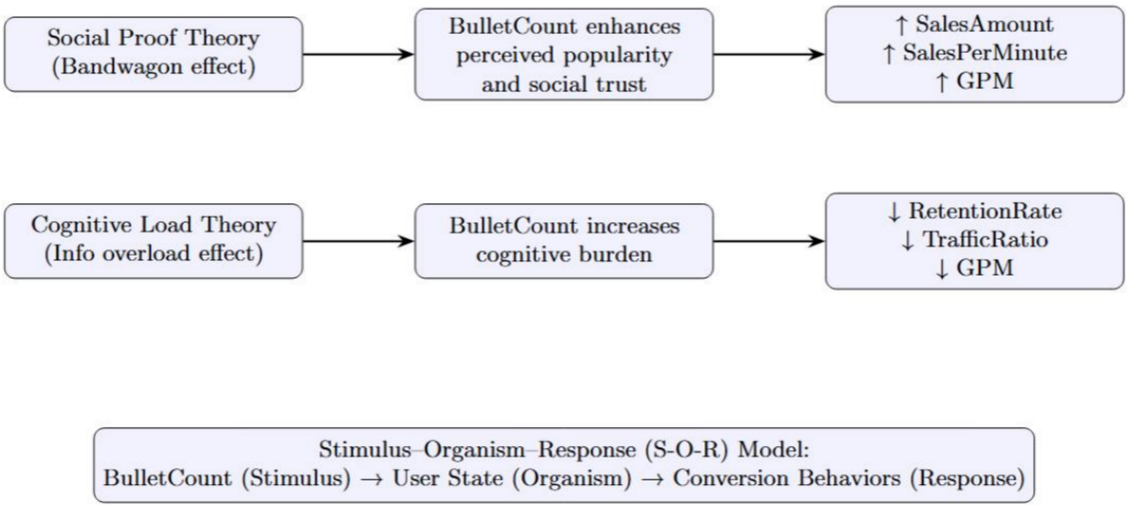

Figure 2. Theoretical Foundation Framework: Dual Role of BulletCount

3.2. Hypothesis Development

3.2.1. Main Effects: Determinants of GPM

To understand conversion efficiency in agricultural livestreams, four key variables are selected: TrafficRatio, RetentionRate, SalesAmount, and SalesPerMinute. These indicators capture different aspects of the livestreaming funnel—from exposure and engagement to transactional intensity(Figure 3).

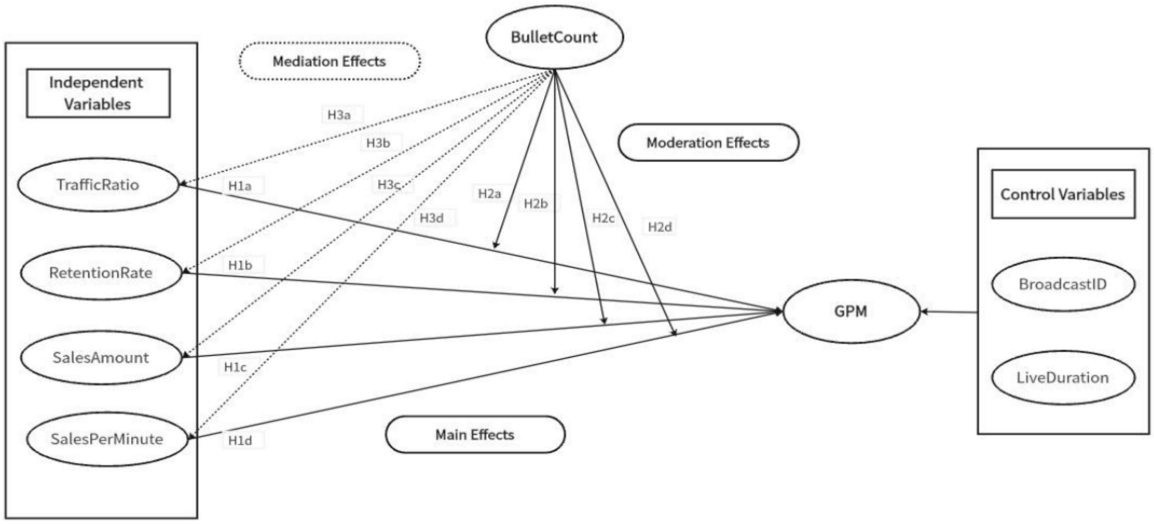

Figure 3. Research model

To understand conversion efficiency in agricultural livestreams, four key variables are selected: TrafficRatio, RetentionRate, SalesAmount, and SalesPerMinute. These indicators capture different aspects of the livestreaming funnel—from exposure and engagement to transactional intensity.

TrafficRatio reflects algorithmic traffic distribution. Zhang and Fu (2024) demonstrate that algorithm-recommended traffic tends to be more targeted and purchase-ready, thereby improving conversion efficiency.

H1a: TrafficRatio positively affects GPM.

RetentionRate measures sustained audience engagement. Peng et al. (2025) reveal that while retention often signals user interest, prolonged exposure in highly interactive environments can induce decision fatigue and reduce purchase efficiency. This finding is consistent with Cognitive Load Theory, which argues that performance declines under excessive information complexity

H1b: RetentionRate negatively affects GPM.

SalesAmount is a direct indicator of transaction volume. Xu et al. (2023) demonstrate that in live-streaming e-commerce, higher sales volumes are closely associated with stronger monetization efficiency. This finding aligns with the "immediacy" and "interactivity" features of live commerce, which can rapidly stimulate consumers' purchase intentions and facilitate transactions.

H1c: SalesAmount positively affects GPM.

SalesPerMinute captures transaction velocity. Tian et al. (2024) reveal that while rapid selling creates urgency and stimulates impulse purchases, it frequently depends on aggressive discounting, which compresses profit margins and reduces overall efficiency.

H1d: SalesPerMinute negatively affects GPM.

3.2.2. Moderating Effects: The Dual Role of BulletCount

In agricultural product livestream e-commerce, bullet comments(BulletCount) have a dual-edged effect on sales outcomes.

On the negative side, Lv and Liu (2022) find that excessive comment density leads to information overload, distracting consumers from key product attributes and reducing decision quality. In agricultural streams, where freshness and traceability require careful explanation, such overload may weaken the effectiveness of algorithmic exposure and sales signals.

H2a. BulletCount negatively moderates the TrafficRatio → GPM relationship.

H2b. BulletCount negatively moderates the SalesAmount → GPM relationship.

On the positive side, Tong et al. (2025) demonstrate that peer-generated comments during livestreams act as social proof signals, enhancing product credibility and consumer trust. Similarly, Gusty et al. (2025) highlight that interactive communication fosters a sense of community, thereby reinforcing purchase intentions. In the agricultural context, timely supportive comments can amplify urgency and strengthen the effects of retention and rapid sales.

H2c. BulletCount positively moderates the RetentionRate → GPM relationship.

H2d. BulletCount positively moderates the SalesPerMinute → GPM relationship.

3.2.3. Mediation Effects: Behavioral Pathways of BulletCount

Beyond moderation, bullet comments may also act as mediators influencing GPM through behavioral pathways.

On the negative side, Lang et al. (2025) show that oversaturation of interactivity discourages new viewers from joining and reduces sustained attention, thereby weakening effective traffic retention. Vogrincic-Haselbacher et al. (2021) further argue that excessive information density imposes cognitive strain, lowering decision-making efficiency.

H3a. BulletCount indirectly reduces GPM by lowering TrafficRatio.

H3b. BulletCount indirectly reduces GPM via RetentionRate.

On the positive side, Ramadhoni and Prassida (2025) demonstrate that interactive engagement significantly boosts perceived social value and purchase likelihood. Colaljo et al. (2024) also confirm that user-generated signals amplify transaction momentum and increase sales.

H3c. BulletCount indirectly increases GPM by boosting SalesAmount.

H3d. BulletCount indirectly increases GPM via SalesPerMinute.

4. Data Measurement

4.1. Hypothesis Development

This study uses Douyin, China's leading short-video and live-streaming platform, as the primary data source. Douyin is chosen for its large user base and its significant role in live-streaming e-commerce, particularly for agricultural content creators and rural revitalization. The platform provides a rich context for studying live commerce dynamics.

Data was collected from Feigua Data (https://www.feigua.cn), a leading third-party analytics platform. The dataset includes viewer counts, BulletCount, sales volumes, GPM, and streamer profiles. It spans 70,640 livestream records from 440 agricultural streamers in 2024. Invalid records were excluded, and continuous variables were log-transformed $\ln(1 + x)$ for normalization.

Control variables like BroadcastID (streamer identifier) and LiveDuration (temporal dimension) were also included to account for streamer and time effects. This approach ensures data accuracy and supports reliable econometric analysis(Figure 4).

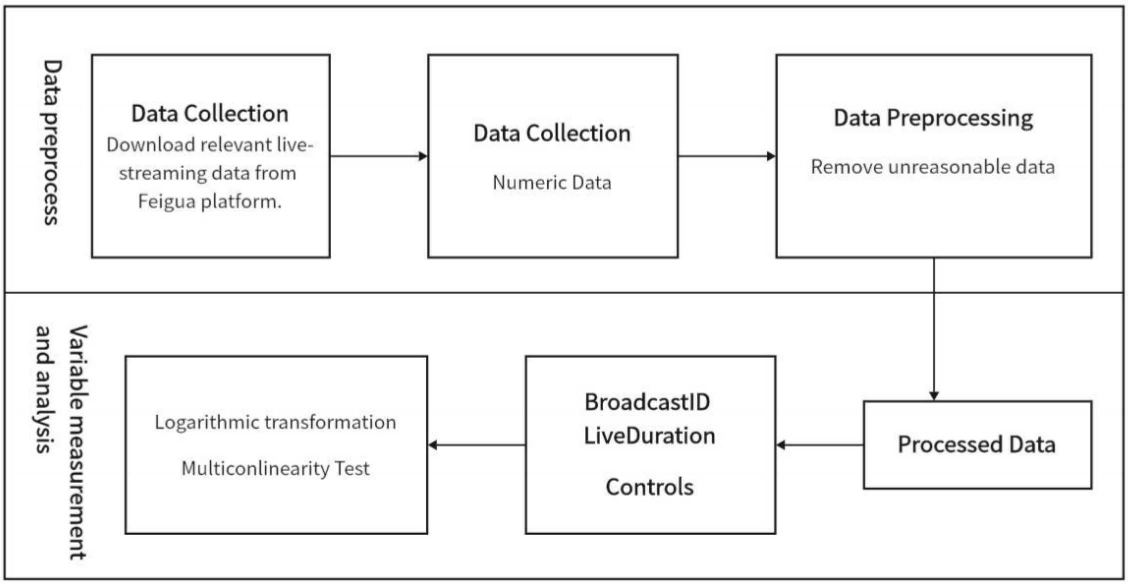

Figure 4. Research model

4.1. Dependent Variable

The dependent variable in this study is GPM, a monetization efficiency indicator widely used in the livestream e-commerce industry. It is calculated as followed.

$$GPM = \left(\frac{\textbf{Total Purchase Amount}}{\textbf{Total Viewers}}\right) \times \mathbf{1000} \qquad \textbf{(1)}$$

GPM represents the total transaction value standardized per 1,000 viewers, allowing for meaningful comparisons across streams of varying sizes and durations. Normalized performance indicators of this kind have been shown to be particularly valuable in live-streaming commerce, where purchasing behavior is shaped not only by audience scale but also by the intensity of interaction and the immediacy of real-time engagement, as discussed in studies by Santos et al. (2023). Because transaction-related metrics often display strong right-skewness and heteroscedasticity, our analysis incorporates a natural logarithmic transformation with a smoothing constant. The use of log transformations as a corrective measure for distributional non-normality has long been established in statistical modeling. This approach also safeguards the interpretability of data containing zero values, which is crucial for downstream regression and structural equation modeling.

4.2. Independent and Mediating Variables

The central independent variable is BulletCount, defined as the total number of bullet comments during a livestream. It captures real-time user engagement and social proof intensity. Higher BulletCount typically reflects elevated interaction density, which may either stimulate purchase intention through urgency cues or suppress conversion due to cognitive overload.

Table 1. The measurements of all variables

Variables	**Name**	**Measurements**
Dependent Variables	GPM	Purchases per thousand view
Independent Variables	TrafficRatio	Proportion of main traffic sources
	RetentionRate	Percentage of retained users
	SalesAmount	Total sales during live
	SalesPerMinute	Sales generated per minute
Control Variables	BroadcasterID	Unique identifier for each broadcaster
	LiveDuration(hours)	Length of the live
Moderator Variables	BulletCount	Number of bullet comments

Table 2. Descriptive statistics of all variables

Variables	**N**	**Mean**	**Std. deviation**	**Min**	**Max**
GPM	70650	1587.41	1901.25	0.00	109802.00
TrafficRatio	70650	0.62	0.15	0.22	1.00
RetentionRate	70650	0.25	0.15	0.02	0.89
SalesAmount	70650	141286.79	786021.26	0.00	49741364.00
SalesPerMinute	70650	777.93	5631.15	0.00	891200.00
BroadcasterID	70650	238.21	127.72	1.00	450.00
LiveDuration	70650	3.83	3.75	0.50	23.93
BulletCount	70650	3665.26	8891.30	0.00	416586.00

Four mediating variables are employed to explore indirect pathways: TrafficRatio shows the main traffic sources' share in a livestream, helping assess reliance on primary channels and audience acquisition efficiency. RetentionRate is viewers' average watch duration, reflecting content engagement. SalesAmount is the total order volume,capturing purchase activity.SalesPerMinute measures orders perminute, indicating sales velocity and processefficiency.

All variables were log-transformed using $\ln(1 + x)$ to mitigate skewness and enable elasticity interpretation within regression coefficients. Table 1 is the measurement of all variables, Table 2 is descriptive statistics of all variables.

4.3. Moderator and Control Variables

BulletCount also serves as a key moderating variable. To test whether comment intensity amplifies or dampens the effects of TrafficRatio, RetentionRate, SalesAmount and SalesPerMinute on GPM, we created four interaction terms. Figure 5 illustrates the empirical distribution of Comments per Minute (CPM) across all sampled live sessions: the bulk of streams cluster below 400 CPM.

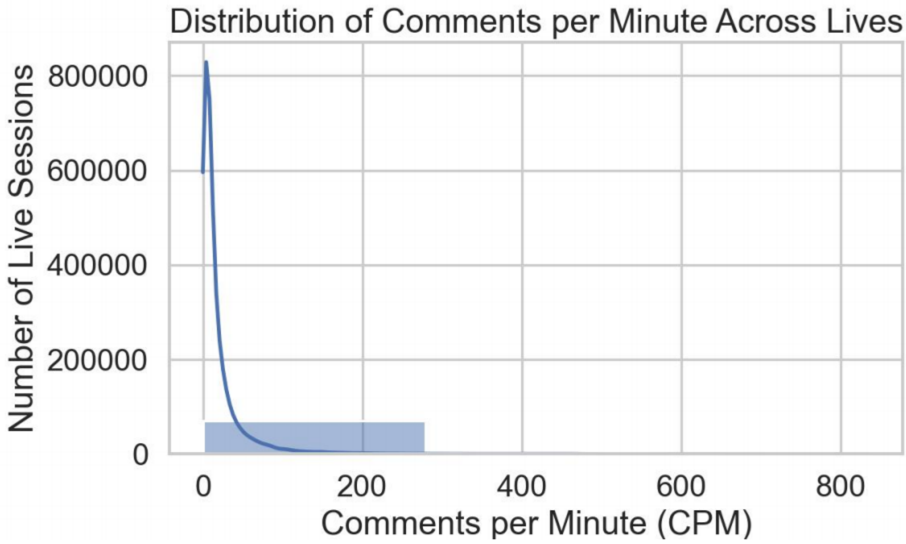

Figure 5. Distribution of Comments per Minute (CPM)

Two control variables are included to safeguard internal validity. LiveDuration is measured as the total length of each session in hours, while BroadcasterID is captured through the platform's unique anchor identifiers. By partialling out time-on-air effects and anchor-specific heterogeneity, these controls isolate the causal impacts of our focal predictors and their moderated relationships.

4.4. Data Analysis

4.4.1. Data Validity and Diagnostic Testing

Prior to model estimation, several diagnostic tests were conducted to ensure the robustness and validity of the data structure for regression and structural equation modeling (SEM).

First, all continuous variables underwent natural-logarithmic transformation via $\ln(1 + x)$ to correct skewness, kurtosis, and heteroscedasticity while preserving zero values. This transformation facilitates elasticity-based coefficient interpretation and aligns with best-practice norms in empirical e-commerce research. The log transformation was additionally employed to systematically mitigate skewed distributions and heteroskedastic disturbances, thereby safeguarding the validity and robustness of model estimates.

Second, multicollinearity was assessed through Variance Inflation Factors (VIFs). All variables reported VIFs below the commonly accepted threshold of 5, indicating no severe multicollinearity.

Third, correlation analysis (Table 3) confirmed acceptable independence among regressors. The absence of excessive correlation among mediators (e.g., RetentionRate vs. TrafficRatio: r = –0.07) strengthens the credibility of multivariate path modeling.

Table 3. Correlation Matrix of Variables

Variables	**GPM**	**Traffic Ratio**	**RetentionRate**	**SalesAmount**	**SalesPerMinute**	**BroadcasterID**	**LiveDuration**	**BulletCount**
GPM	1							
TrafficRatio	-0.25	1						
RetentionRate	0.01	-0.07	1					
SalesAmount	0.51	0.05	0.34	1				
SalesPerMinute	0.29	-0.06	0.36	0.61	1			
BroadcasterID	0.25	-0.01	-0.13	-0.25	-0.20	1		
LiveDuration	0.25	-0.00	-0.09	0.33	-0.10	0.02	1	
BulletCount	0.04	-0.05	0.49	0.72	0.50	-0.16	0.29	1

To account for possible endogeneity due to unobserved time-invariant heterogeneity (e.g., streamer charisma, channel quality), we implemented two-way fixed-effects (TWFE) modeling with BroadcasterID and LiveDuration as control factors. This design addresses omitted variable bias and self-selection concerns.

4.4.2. Data Validity and Diagnostic Testing

The multiple linear regression model was formulated as follows.

$$\ln(1+GPM_{it}) = \beta_0 + \beta_1 \ln(1+TrafficRatio_{it}) + \beta_2 \ln(1+RetentionRate_{it}) + \beta_3 \ln(1+SalesAmount_{it}) + \beta_4 \ln(1+SalesPerMinute_{it}) + \beta_5 \ln(1+BulletCount_{it}) + \beta_6 \ln(1+TrafficRatio_{it}) \times \ln(1+BulletCount_{it}) + \beta_7 \ln(1+RetentionRate_{it}) \times \ln(1+BulletCount_{it}) + \beta_8 \ln(1+SalesAmount_{it}) \times \ln(1+BulletCount_{it}) + \beta_9 \ln(1+SalesPerMinute_{it}) \times \ln(1+BulletCount_{it}) + \alpha_i + \lambda_t + \varepsilon_{it} \quad (2)$$

In Equation, $ln(1+GPM_{it})$ is dependent variable; $(\ln(1+TrafficRatio_{it}))$, $(\ln(1+RetentionRate_{it}))$, $(\ln(1+SalesAmount_{it}))$ and $(\ln(1+SalesPerMinute_{it}))$ are independent variables; $(\ln(1 + TrafficRatio_{it}) \times \ln(1 + BulletCount_{it}))$, $(\ln(1 + RetentionRate_{it}) \times \ln(1 + BulletCount_{it}))$, $(\ln(1 + SalesAmount_{it}) \times \ln(1 + BulletCount_{it}))$ and $(\ln(1 + SalesPerMinute_{it}) \times \ln(1 + BulletCount_{it}))$; (α_i) is individual fixed effect, (λ_t) is time fixed effects, $(\ln(1 + BulletCount_{it}))$ is the dummy variable; and (ϵ_{it}) is random error.

This log-linear functional form allows for elasticity interpretation and mitigates distributional issues in high-variance transactional datasets. Estimation was conducted in Python using the "linear models" package under robust standard error assumptions. Clustered standard errors at the streamer level ensure consistent inference under within-entity correlation.

To supplement the regression findings and test causal pathways, Bootstrap-based Structural Equation Modeling (SEM) was employed using 5,000 resamples under the bias-corrected and accelerated (BCa) method. This approach provides non-parametric estimates of indirect effects, accommodating non-normal mediator distributions and ensuring inference validity.

5. Result

5.1. Regression Analysis

To empirically assess the proposed hypotheses, a two-way fixed effects regression analysis was conducted using Python. The model yielded an R-squared value of 0.528, indicating that approximately 52.8% of the variance in GPM can be explained by the independent and moderating variables included in the model. Additionally, the F-test statistic was highly significant ($F = 361.61$, $p < 0.001$), suggesting a strong overall model fit and affirming the robustness of the regression framework for capturing the key drivers of profitability in the context of agricultural livestream commerce.

The main effects show a mixed pattern. TrafficRatio ($\beta = 2.801$, $p = 0.229$) did not significantly affect GPM, so Hypothesis H1a is not supported. RetentionRate negatively impacted GPM ($\beta = -4.142$, $p = 0.041$), supporting H1b, which suggests that longer viewer retention might not always translate to higher profits. SalesAmount had a strong positive effect ($\beta = 5.266$, $p < 0.001$), supporting H1c, indicating higher sales volumes correspond to increased GPM, confirming that transaction scale directly enhances monetization efficiency in livestream ecosystems.. SalesPerMinute negatively affected GPM ($\beta = -0.659$, $p < 0.001$), supporting H1d, indicating that rapid sales bursts may reduce margins, possibly due to discounting or inefficiencies.

Regarding moderating effects, BulletCount exhibited a complex role. It negatively moderated the effects of TrafficRatio ($\beta = -1.537$, $p < 0.001$) and SalesAmount ($\beta = -0.189$, $p < 0.001$) on GPM, supporting H2a and H2b, suggesting that intense viewer interaction may weaken these positive effects. Conversely, BulletCount positively moderated RetentionRate ($\beta = 0.675$, $p = 0.009$) and SalesPerMinute ($\beta = 0.157$, $p < 0.001$), supporting H2c and H2d, enhancing their positive influence on profitability. Together, these moderating effects reveal a nuanced and dual role of BulletCount—it can either dilute or enhance conversion efficiency depending on the nature of the underlying pathway. The detailed regression results are reported in Table 4.

Table 4. Two-Way Fixed Effects Regression

Category	Pathway	Coef.	Std.Err.	T	P	Sig.	Support
Main effect	Constant	26.881	1.842	14.591	0.000	***	N/A
	H1a TrafficRatio→GPM	2.801	2.308	1.217	0.229		No
	H1b RetentionRate→GPM	-4.142	2.024	-2.046	0.041	**	Yes
	H1c SalesAmount→GPM	5.266	0.274	19.198	0.000	***	Yes
	H1d SalesPerMinute→GPM	-0.659	0.172	-3.832	0.000	***	Yes
Moderating effect	H2a TrafficRatio × BulletCount→GPM	-1.537	0.314	-4.895	0.000	***	Yes
	H2b RetentionRate × BulletCount→GPM	0.675	0.257	2.629	0.009	**	Yes
	H2c SalesAmount × BulletCount→GPM	-0.189	0.035	-5.382	0.000	***	Yes
	H2d SalesPerMinute × BulletCount→GPM	0.157	0.026	6.016	0.000	***	Yes
Summary	R-squared	0.528			Number of obs	70650	
	F-test	361.61			Prob>F	0.000	

Robust standard errors.***p<0.01; **p<0.05; *p<0.1

5.2. OLS-Based Moderation Analysis

Figure 6a illustrates a nuanced interaction between BulletCount and TrafficRatio on GPM. Specifically, when BulletCount is low, the negative effect of TrafficRatio on GPM becomes more pronounced, intensifying the suppression of profitability at lower levels of TrafficRatio. Conversely, at higher levels of BulletCount, this suppressive effect is further amplified when TrafficRatio is high, suggesting that an abundance of real-time comments exacerbates the diminishing returns of traffic exposure on gross profit margin.

Similarly, Figure 6c highlights the moderating role of BulletCount in the SalesAmount-GPM relationship. The steeper negative slope under low BulletCount conditions indicates that SalesAmount exerts a stronger suppressive impact on GPM when viewer engagement via

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comments is limited. This suggests that without active interaction, increased sales volume may come at the cost of reduced profit margins, possibly due to aggressive discounting or operational inefficiencies.

In contrast, Figure 6b and Figure 6d reveal that higher BulletCount significantly strengthens the positive associations of RetentionRate and SalesPerMinute with GPM, respectively. The steeper slopes under high engagement conditions confirm that interactive environments enhance the beneficial effects of audience retention and transactional intensity on profitability. These patterns corroborate the positive moderating role of BulletCount in fostering effective conversion behaviors when viewer engagement is high.

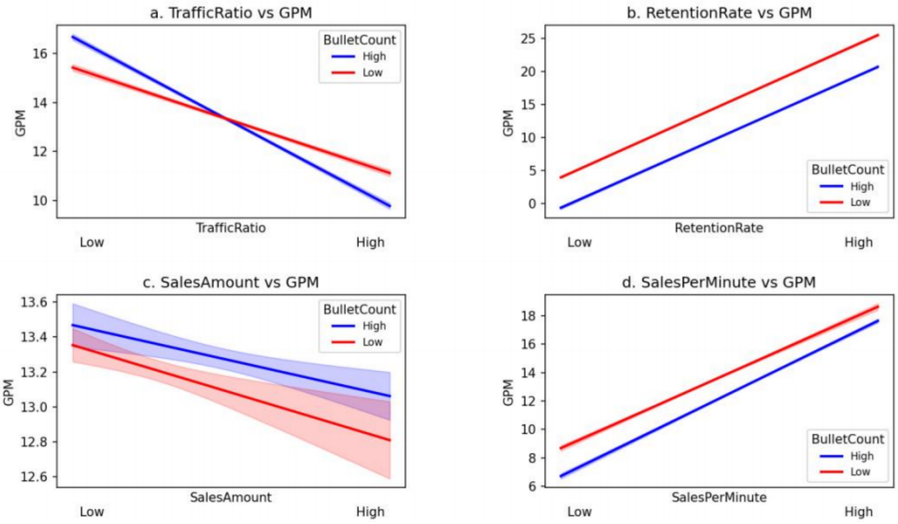

Figure 6. Moderating Effect of Bullet Comments

5.3. Robustness Validation

The robustness of the regression analysis was systematically examined using three complementary methodological approaches to ensure the reliability of the findings. First, the dependent variable, GPM, was adjusted by applying a 10% upward scaling factor (× 1.1). This modification served to test the model's sensitivity to changes in the outcome measure. The results demonstrated remarkable stability, with the adjusted model achieving an R-squared value of 0.540, explaining 54% of the variance in the rescaled GPM. This consistency indicates that the model's explanatory power remains strong even under moderate transformations of the dependent variable.

Second, robustness was further validated by manipulating one of the key independent variables, TrafficRatio, through a 10% reduction (× 0.9). This respecification produced an identical R-squared value (0.540), confirming that the model's fit and predictive capacity are not unduly sensitive to small adjustments in predictor measurements. Additionally, a more stringent robustness check was conducted by excluding extreme observations: the top and bottom 1% of the sample distribution were truncated, reducing the sample size from 70,650 to 69,231. Despite this reduction, the model maintained a solid performance with an R-squared of 0.512. This resilience suggests that the regression framework is robust to the influence of outliers or distributional irregularities. Collectively, these sensitivity analyses (Table 5) underscore the robustness and reliability of the analytical framework across diverse scenarios.

Table 5. Robustness Test

Variable	FE	Replace IV	Truncate 1%
TrafficRatio	3.099	NaN	2.882
RetentionRate	-4.572*	-4.156*	-4.122*
SalesAmount	5.806* * *	5.278* * *	5.246* * *
SalesPerMinute	-0.731* * *	-0.664* * *	-0.765* * *
BulletCount	-1.891* * *	-1.719* * *	-1.786* * *
TrafficRatio × BulletCount	-1.693* * *	-1.539* * *	-1.519* * *
RetentionRate × BulletCount	0.746* *	0.678* *	0.669* *
SalesAmount × BulletCount	0.210* * *	-0.191* * *	-0.191* * *
SalesPerMinute × BulletCount	0.174* * *	0.158* * *	0.170* * *
Constant	29.610* * *	26.918* * *	27.328* * *
Control Variables	Yes	Yes	Yes
Entity Effects	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes
Sample Size	70650	70650	69231
R-squared	0.540	0.540	0.512

Robust standard errors.***p<0.01; **p<0.05; *p<0.1

5.4. Effect Size Interpretation

To complement statistical significance, we interpret the practical magnitude of key coefficients based on elasticity. A 1% increase in SalesAmount leads to a 5.27% rise in GPM, indicating that higher transaction volume directly enhances monetization efficiency. In contrast, a 1% increase in RetentionRate results in a 4.14% decline in GPM, supporting the cognitive load hypothesis—longer viewing may reduce purchase conversion.

The main effect of BulletCount is negative: each 1% increase corresponds to a 1.89% drop in GPM. However, interaction terms reveal conditional effects. In high SalesPerMinute streams, BulletCount slightly improves GPM by 0.16% per 1% increase, while in high TrafficRatio sessions, it significantly reduces GPM by 1.54% per 10% increase. These results highlight

BulletCount's dual role: it amplifies GPM during time-sensitive promotions, validating its urgency-inducing function in agricultural sales bursts. But excessive comment volume may distract users and lower conversion, especially in attention-heavy traffic environments(Table 6).

Table 6. Marginal Effects Comparison Table (Based on 10% Change in Each Variable

Variable	% Change	Coefficient (β)	Marginal Effect on GPM
SalesAmount	+10%	5.266	+0.502
RetentionRate	+10%	–4.142	–0.395
TrafficRatio	+10%	2.801	+0.267
SalesPerMinute	+10%	–0.659	–0.063
BulletCount (main effect)	+10%	–1.891	–0.180
BulletCount × TrafficRatio	+10%	–1.537	–0.146
BulletCount × RetentionRate	+10%	+0.675	+0.064
BulletCount × SalesAmount	+10%	–0.189	–0.018
BulletCount × SalesPerMinute	+10%	+0.157	+0.015

6. Mediation Effects of BulletCount

6.1. Mediation Analysis

The study employed a bootstrap-mediated structural equation model to assess the indirect pathways through which BulletCount influences GPM. Following the Bootstrap-ABC (Bias-Corrected and Accelerated) method, mediation effects $(a \times b)$ were estimated through nonparametric resampling, with bias-adjusted 95% confidence intervals derived from the percentile distribution of indirect effect estimates. This approach revealed four distinct mediation mechanisms.

The Bootstrap-ABC method identified four mediation pathways of BulletCount on GPM. In the TrafficRatio path, BulletCount indirectly reduced GPM (β = 0.05) via lowering TrafficRatio, supporting H3a. Through RetentionRate, it indirectly decreased GPM (β= -0.09), aligning with H3b. Via SalesAmount, BulletCount boosted GPM (β = 3.03), supporting H3c. Lastly, the SalesPerMinute path showed a positive indirect effect (β= 0.75), indicating support for H3d (Table 7).

First, BulletCount suppressed GPM indirectly by reducing TrafficRatio (β= -0.00**, β= -14.71*); indirect effect β= 0.05), with no direct effect observed. Second, while BulletCount enhanced RetentionRate (β= 0.04**)), this mediator paradoxically lowered GPM (β= -2.15*}), resulting in a net negative indirect effect (β = -0.09). Third, the SalesAmount pathway demonstrated amplification: BulletCount increased SalesAmount (β= 0.54**), which strongly elevated GPM (β= 5.65*), yielding a significant positive indirect effect (β= 3.03). Finally, the SalesPerMinute pathway exhibited competitive mediation: despite BulletCount's positive effect on SalesPerMinute (β= 0.52**) and its GPM-enhancing role (β = 1.45*), the indirect effect was positive (β= 0.75)(Figure 7).

Table 7. Indirect Effects of BulletCount on GPM Through Different Mediators

Pathway	Direct Effect	Indirect Effect	Total Effect	Support
H3a BulletCount→TrafficRatio→GPM	β = 0.11	β = 0.05	β = 0.16	Yes
H3b BulletCount→RetentionRate→GPM	β = 0.25	β = −0.09	β = 0.16	Yes
H3c BulletCount→SalesAmount→GPM	β = −2.87	β = 3.03	β = 0.16	Yes
H3d BulletCount→SalesPerMinute→GPM	β = −0.59	β = 0.75	β = 0.16	Yes

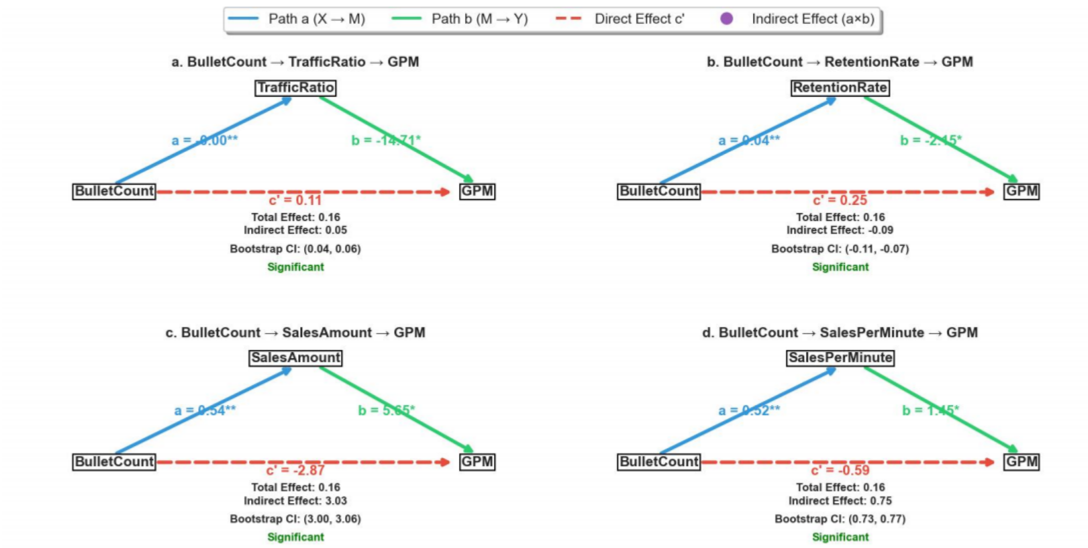

Figure 7. Mediation Effect

Structural equation modeling was employed to delineate the mechanistic pathways through which the core variable (BulletCount) influences the target metric (GPM) via four distinct mediators. The analysis demonstrated that BulletCount exerted significant positive effects on TrafficRatio (β=0.05, 95% CI [0.04, 0.06]), SalesAmount (β=3.03, CI [3.00, 3.06]), and SalesPerMinute (β=0.75, CI [0.73, 0.77]), while generating a robust negative association with RetentionRate (β=-0.09, CI [-0.11, -0.07]).

6.2. Dual Transmission Mechanisms

Structural equation modeling was employed to delineate the mechanistic pathways through which the core variable (BulletCount) influences the target metric (GPM) via four distinct mediators. The analysis demonstrated that BulletCount exerted significant positive effects on

TrafficRatio (β=0.05, 95% CI [0.04, 0.06]), SalesAmount (β=3.03), CI [3.00, 3.06]), and SalesPerMinute (β=0.75, CI [0.73, 0.77]), while generating a robust negative association with RetentionRate (β=-0.09, CI [-0.11, -0.07]).

Path decomposition analyses revealed distinct and polarized mediating effects on GPM. SalesAmount emerged as the strongest positive mediator (β= 5.65), underscoring the vital role of total sales volume in driving profitability. SalesPerMinute also positively influenced GPM (β = 1.45), indicating that higher transaction intensity enhances gross margins. Conversely, TrafficRatio (β= -14.71) and RetentionRate (β = -2.15) showed significant suppressive effects. These findings suggest that while increasing traffic and retaining viewers are generally desirable, in this context they may incur additional costs or inefficiencies that reduce profit margins.

This multi-mediation framework highlights BulletCount's dual transmission mechanisms. Positively, BulletCount amplifies conversion through pathways associated with sales volume, transaction speed, and effective traffic utilization. Negatively, it triggers a compensatory suppression effect via user retention, possibly reflecting information overload or reduced conversion efficiency in prolonged engagement. Together, these opposing effects illustrate the complex balance BulletCount maintains in influencing GPM, as summarized in Figure 8. This nuanced understanding enriches the theoretical foundation for interpreting how interactive features shape economic outcomes in livestream commerce.

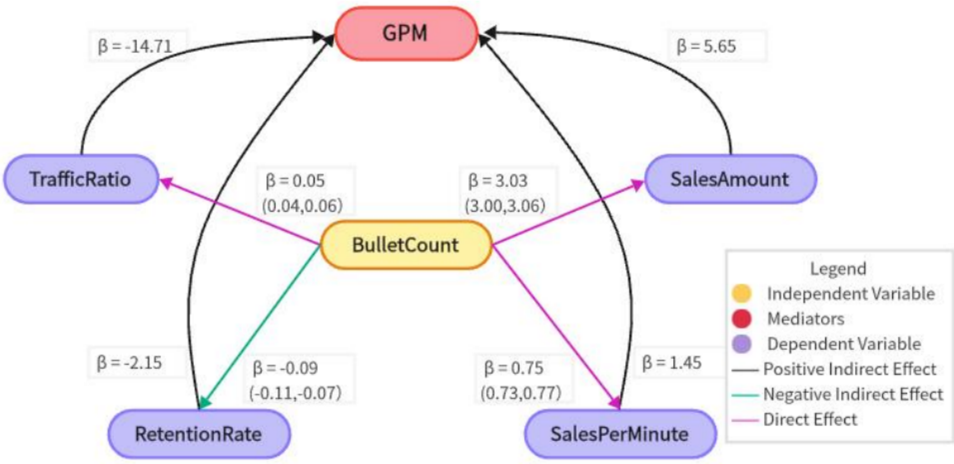

Figure 8. BulletCount's Mediation Effects on GPM Pathways Diagram.

7. Discussion and Implications

7.1. Extended Discussion

This study reveals the nuanced duality of bullet comments (BulletCount) in agricultural livestream commerce. While SalesAmount emerged as the strongest direct driver of GPM—underscoring transaction volume's primacy in rural monetization—the negative impacts of RetentionRate and SalesPerMinute highlight critical trade-offs. Prolonged viewing may induce decision fatigue among agricultural consumers evaluating complex attributes (e.g., freshness, pesticide use), diminishing marginal returns on engagement. Similarly, rapid-fire sales tactics often erode margins through discount dependency, particularly problematic for perishable goods with narrow profit windows. Notably, TrafficRatio's non-significance challenges conventional platform logic, suggesting algorithmic traffic alone cannot overcome trust deficits inherent to agricultural transactions without substantive interaction.

BulletCount's moderating role further demonstrates context-dependent efficacy. Its attenuation of TrafficRatio and SalesAmount effects aligns with cognitive load theory: comment floods during product explanations obscure critical details (e.g., organic certifications), impairing informational clarity. Conversely, its amplification of RetentionRate and SalesPerMinute benefits reflects social proof dynamics—real-time endorsements ("This village's peaches are authentic!") validate quality during high-engagement phases, accelerating time-sensitive decisions for seasonal produce. This threshold-sensitive duality necessitates precision in deployment.

Mediation pathways confirm behavioral complexity. Negative indirect effects via TrafficRatio and RetentionRate indicate that excessive comments can fragment attention, degrading traffic quality and conversion potential during informational segments. Excessive comment density degrades traffic-to-sales conversion, as cognitive overload diverts attention from core product information during high-exposure phases. Positively, BulletCount's reinforcement of SalesAmount and SalesPerMinute pathways demonstrates its capacity to compress decision cycles through collective urgency—a vital mechanism for mitigating spoilage risks in agricultural supply chains. Collectively, these findings establish an integrated behavioral-cognitive framework where BulletCount's net impact hinges on strategic alignment with livestream objectives and agricultural product characteristics.

7.2. Extended Theoretical Implications

First, it advances Social Proof Theory by showing how BulletCount operates as a real-time trust signal under high uncertainty. Social proof was first conceptualized by Deutsch and Gerard (1955) as reliance on others' opinions under ambiguous conditions, and later expanded by Cialdini (2007) to explain how individuals use popularity cues in decision-making. Within agricultural livestreams, however, comment volume does more than indicate popularity: it functions as distributed credibility validation. For instance, remarks such as "I know Farmer Li's orchard" transform comment density into place-based authenticity. This aligns with research on digital trust in rural e-commerce by Wang and Zhang (2023). Thus, social proof in this context is redefined as a marker of origin-based credibility, directly addressing rural information asymmetry.

Second, the study situates Cognitive Load Theory within the unique context of agricultural livestreaming. Sweller (1994) formulation of the theory emphasized the limits of working memory, a point elaborated by Paas and van Merriënboer (1994). Our findings suggest that dense comment streams intensify these constraints, especially when consumers must simultaneously evaluate complex product attributes such as organic certification, shelf life, and logistics. Recent evidence by Luo et al. (2020) also shows that interactive comment density in livestream settings can increase cognitive processing costs. Building on these foundations, our work refines Cognitive Load Theory for perishable goods commerce, underscoring the need for cognitive resource allocation models tailored to agriculture's information-intensive environments.

Third, this research enriches the Stimulus-Organism-Response paradigm by unpacking BulletCount's dual affective-cognitive pathways. Mehrabian and Russell (1974) introduced the S-O-R framework to explain how environmental stimuli shape emotional and behavioral responses. More recently, Guo et al. (2021) applied the model to livestream commerce, highlighting the behavioral impact of social cues. Within agricultural livestreaming, comments act as stimuli that elicit antagonistic organismic states: affective arousal, such as urgency to secure seasonal harvests, and cognitive tension, such as overload when processing fragmented technical explanations. These competing responses — accelerated purchases versus disengagement — reveal a unified mechanism for explaining behavioral variance in this domain.

Finally, we introduce a novel dual-channel framework that reconciles the inherent paradoxes of interactive commerce. The synergy path leverages social cues to accelerate conversion, while the compensatory path imposes cognitive costs that erode efficiency. By reconceptualizing BulletCount as an endogenous, sign-switching moderator — rather than a uniformly positive or negative force—the framework resolves inconsistencies in the extant literature. Integrating Social Proof and Cognitive Load theories through a context-sensitive lens, it fills a critical gap in research on agricultural digital consumption and delivers a portable analytical framework for platform design, enabling the maintenance of an optimal incentive-affordability equilibrium when both information complexity and interaction density escalate.

7.3. Practical Implications

This study provides actionable strategies for stakeholders to optimize agricultural livestream commerce through strategic management of bullet comments (BulletCount). For streamers and MCN agencies, we recommend dynamically regulating comment density across livestream phases. During detailed product presentations—particularly for information-intensive items like organic produce or traceable goods — reducing BulletCount minimizes cognitive overload, sustaining viewer focus on critical attributes. Conversely, in promotional segments such as flash sales, actively encouraging high-volume comments leverages social proof and urgency cues to stimulate impulse purchases. Implementing rhythmic alternation between low- and high-engagement intervals creates a balanced cognitive-behavioral flow, enhancing overall GPM efficiency. Training in real-time moderation tools further empowers streamers to maintain this optimal rhythm, particularly valuable for rural producers with limited technical resources.

For platform developers, findings underscore the need for context-aware interaction systems. AI-driven bullet comment filters could adaptively reduce visual noise during technical explanations while preserving social proof during promotional segments. Developing agriculture-specific interface templates (e.g., standardized layouts for perishables) lowers operational barriers for novice rural streamers. These innovations balance informational clarity with interactive vitality, addressing the dual role of comments as both conversion catalysts and cognitive disruptors identified in our analysis. Such technical enhancements directly support scalable rural e-commerce integration.

Policymakers should shift from infrastructure provision to operational capacity-building like training in engagement strategies. Targeted workshops on engagement pacing and cognitive load management — tailored to agricultural contexts like seasonal promotions — can empower rural content creators. Financial incentives (e.g., subsidies or tax breaks) for platforms embedding smart moderation tools (e.g., sentiment-based comment ranking) would accelerate adoption. Complementarily, certification schemes recognizing “Low Cognitive Load Livestream” practices could establish industry standards. These interventions foster sustainable digital ecosystems where optimized interactivity advances broader rural revitalization goals through efficient market linkages.

8. Limitations and Future Research

While this study advances understanding of interactive dynamics in agricultural livestream commerce, five limitations warrant scholarly attention.

First, platform dependency constrains generalizability. Exclusive reliance on Douyin data — characterized by algorithm-driven traffic and urban-dominated demographics — ignores platform heterogeneity. Kuaishou’s grassroots user base favors rural authenticity narratives, while Taobao Live integrates supply-chain tools affecting purchase friction. Future work should conduct cross-platform experiments comparing BulletCount effects under varying algorithmic logics (e.g., Douyin’s entertainment-centric feeds vs. Taobao’s transaction-oriented interfaces). Such comparisons could reveal how platform architectures modulate cognitive-social trade-offs in rural e-commerce.

Second, agricultural exceptionalism limits category transferability. While perishability and traceability demands amplify cognitive load in our context, hedonic goods (e.g., handicrafts) may prioritize emotional contagion via comments, and branded products could leverage comments for prestige signaling. Future research should establish a taxonomy of product attributes (perishability, information intensity, credence qualities) to predict BulletCount’s dual-role boundaries. Testing whether social proof dominates for low-involvement crops (e.g., potatoes) versus cognitive load for high-stakes goods (e.g., organic infant food) would refine agricultural segmentation strategies.

Third, methodological constraints obscure temporal dynamics. Though two-way fixed effects control time-invariant confounders, they cannot capture streamer-viewer coevolution: as farmers gain experience, they may strategically time comment surges during promotions while suppressing them during explanations. Longitudinal field experiments manipulating BulletCount density across seasons (e.g., harvest vs. off-seasons) could quantify learning effects. Quasi-experimental designs exploiting platform policy shifts (e.g., Douyin’s 2023 comment-filtering rollout) would further strengthen causal claims.

Fourth, inferred psychological mechanisms lack empirical validation. Cognitive overload and social proof remain theoretical constructs without direct measurement. Integrating multimodal biometrics could resolve this: eye-tracking during pesticide disclosure segments would quantify visual attention theft by comment floods; EEG during scarcity promotions could neural signature urgency responses to social proof cues. Complementarily, structured surveys assessing trust in geo-tagged comments (e.g., “I trust comments vouching for local farmers”) would ground social proof theory in agricultural contexts.

Fifth, the blunt arithmetic of comment counts erases the layered semantics, temporal cadence, and heterogeneity of voices that co-produce trust and conversion in agricultural e-commerce; future work must therefore decode these semantic dimensions of engagement—sentiment valence, temporal clustering — through NLP methods to qualify BulletCount’s impact. BulletCount collapses the phenomena into a single scalar, yet a purpose-built machine-learning pipeline can surface sentiment-weighted engagement in which a surge of logistics-related negativity instantaneously corrodes perceived reliability, time-locked comment bursts that ride the wave of flash-discount announcements and momentarily inflate SalesPerMinute, and the divergent persuasive force of verified farmer endorsements relative to probing questions from urban buyers. Capturing these effects demands a domain-specific NLP lexicon that interweaves freshness descriptors, cultivar-centric dialects, and socio-linguistic markers, thereby enabling granular moderation analyses that illuminate how nuanced comment quality dynamically recalibrates GPM pathways across heterogeneous rural marketplaces

Collectively, these limitations demarcate critical frontiers for advancing agricultural livestream commerce research. Rather than constraining our findings, they illuminate pathways to develop context-aware interaction frameworks that reconcile platform diversity, product heterogeneity, and behavioral dynamics inherent to rural digitization. Addressing these gaps through cross-platform field trials, biometric validation, and agricultural NLP pipelines will transform bullet comments from mere engagement metrics into precision tools for reducing cognitive friction and amplifying place-based trust. Such innovations promise to elevate livestreaming beyond sales facilitation toward a sustainable infrastructure for knowledge exchange—empowering farmers to navigate information asymmetry while connecting consumers to agricultural narratives. Future research embracing these directions will not only refine theoretical models of digital engagement but also co-create actionable standards for platform design, streamer training, and policy formulation, ultimately accelerating digitally inclusive rural revitalization.

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