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How real-time interaction drives purchase intention: the mediating pathway through perceived trust in live streaming

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Abstract

Purpose – Live-streaming e-commerce is characterized by real-time interaction, namely, consumer-streamer interaction (CSI) and consumer-consumer interaction (CCI). Integrating uses and gratifications theory (UGT) and the Elaboration Likelihood Model (ELM), this study proposes a dual-process framework of trust formation: CSI (expertise and responsiveness) cultivates trust through the central route by enabling evaluation of information quality, whereas CCI (personalization and entertainment) cultivates trust through the peripheral route by leveraging social proof and emotional resonance.

Design/methodology/approach – Using survey data from 409 live-streaming shoppers in China and employing partial least squares structural equation modeling (PLS-SEM), this study examines how CSI and CCI shape purchase intention via perceived trust, and how price sensitivity moderates the trust-purchase intention relationship.

Findings – CSI and CCI enhanced purchase intention through perceived trust, with indistinguishable baseline effects. Trust partially mediated these associations, with central and peripheral patterns. Price sensitivity eliminated personalization's direct effect, suggesting comparable effects may conceal mechanistic differences. Furthermore, heightened sensitivity induced systematic processing, reducing reliance on trust and moderating the perceived trust–purchase intention relationship.

Originality/value – This study advances live-streaming research by embedding dual-process theory within real-time interaction dynamics. Contributions include demonstrating equivalent effects can operate through divergent mechanisms, reconceptualizing streamer expertise as a dynamically validated signal, and empirically testing ELM's boundary conditions, showing peripheral-route effectiveness depends on low motivation (proxied by price sensitivity). Findings extend ELM to live-streaming and offer actionable guidance for interaction strategy design.

Keywords Live streaming, Real-time interaction, Perceived trust, Uses and gratifications theory, Elaboration likelihood model

Paper type Research article

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1. Introduction

Live-streaming e-commerce has reshaped how consumers acquire information through real-time interaction, emerging as a key growth engine in digital retail. By 2025, China's live-streaming users had exceeded 833 million, with transaction volumes surpassing RMB 5 trillion, accounting for one-third of total online retail sales (China Internet Network Information Center, 2025; State Administration for Market Regulation, 2026). However, rapid growth has not eased consumers' trust concerns; trust remains a bottleneck constraining further development. Thus, understanding and cultivating consumer trust in the live-streaming context has become a core issue for both academia and industry.

Real-time interaction is the core competitive advantage of live-streaming (Xue *et al.*, 2020) and can be distinguished into two forms: consumer-streamer interaction (CSI) and consumer-consumer interaction (CCI). The former reduces information asymmetry through professional demonstrations and timely responses, enabling consumers to directly assess the streamer's expertise and responsiveness (Joo and Yang, 2023). The latter involves experienced consumers sharing product experiences and recommendations via danmaku thereby reinforcing social bonds and enhancing consumers' perceived personalization and entertainment value (Fan *et al.*, 2024). Together, these two interaction types form the basis for consumer trust in the live-streaming.

Yet, literature leaves three important questions unresolved. First, CSI and CCI have been examined in isolation (Gu *et al.*, 2023), leaving their comparative mechanisms undertheorized. Second, expertise has predominantly been treated as a static characteristic, with limited consideration of how it may function as a dynamic signal that consumers actively assess and validate through real-time interaction (Li *et al.*, 2025). Third, prior research has not examined whether these interaction types foster trust through distinct cognitive routes, a distinction that carries theoretical weight given the Elaboration Likelihood Model's (ELM) prediction that central and peripheral-route trust differ in durability (Petty and Cacioppo, 1986). Accordingly, this study addresses the following research questions:

> Q1: How do CSI and CCI differentially influence consumer trust in live-streaming e-commerce?
>
> Q2: How does perceived trust affect purchase intention, and how does price sensitivity moderate this effect?

To answer these questions, this study integrates Uses and Gratifications Theory (UGT) with ELM. UGT identifies consumers' core motivations for engaging in live streaming (Fu *et al.*, 2024), whereas ELM explains how the fulfillment of different needs translates into persuasion through its central and peripheral routes (Petty and Cacioppo, 1986). Drawing on this framework, this study proposes that CSI activates the central route, building trust through careful evaluation of information quality. Specifically, expertise is reconceptualized as a dynamically validated signal: credibility is established when knowledge is mobilized in real time and publicly tested, with responsiveness reflecting the streamer's capacity for timely and substantive replies. In contrast, CCI activates the peripheral route, building trust through heuristic cues: personalization (trust in peers transfers to the streamer) and entertainment (positive affect spills over to purchase decisions). This study further tests the boundary conditions of peripheral-route persuasion using price sensitivity as a proxy for processing motivation.

This study makes three contributions. First, it advances understanding of consumer persuasion by demonstrating statistical equivalence does not imply mechanistic equivalence. Although the effects of different interaction types on trust and purchase intention were statistically comparable, price sensitivity as a moderator reveals a mechanistic difference between the peripheral and central routes.

Second, departing from the traditional view of expertise as a static attribute, this study reconceptualizes it as a dynamic signal that must be validated through real-time interaction.

Drawing on signaling theory (Spence, 1973), expertise and responsiveness are shown to independently contribute to trust formation.

Third, it extends ELM to live-streaming (Luo *et al.*, 2024a) and supports its core prediction that the peripheral route loses effectiveness when processing motivation is high.

2. Literature review

2.1 Live streaming shopping

Existing research has examined the antecedents of purchase intention in live-streaming from two perspectives: streamer characteristics and live-streaming content features. Streamer characteristics include streamer-product fit (Park and Lin, 2020), linguistic features and speech acts (Chen *et al.*, 2023), attractiveness and communication styles (Guo *et al.*, 2022), and professional competence (Li *et al.*, 2025). Live-streaming content feature research has focused on how time pressure and immersive experiences drive impulse purchase behavior (Hao and Huang, 2025). However, these two perspectives have largely overlooked live-streaming's defining feature: real-time interaction.

A growing body of research has begun to acknowledge real-time interaction as a distinct construct, differentiating between CSI and CCI. CSI centers on information quality, driving behavior through the satisfaction of cognitive needs, the cultivation of trust, and the formation of parasocial relationships (Gu *et al.*, 2023; Zhang *et al.*, 2022; Ma *et al.*, 2024). By contrast, CCI emphasizes emotional contagion, fostering a sense of community, enhancing social presence, and amplifying herd behavior (He *et al.*, 2026; Chen *et al.*, 2025). Scholars have extended research to explore micro-level phenomena such as danmaku consistency and emotional contagion (Zhang and Ruan, 2024; Kim *et al.*, 2026), corroborating the distinction between informational and emotional communication strategies (Luo *et al.*, 2024b).

Despite these contributions, three substantive gaps remain. First, no study has directly contrasted the mechanisms by which CSI and CCI steer consumer behavior. Second, prior research has largely characterized expertise as a static attribute (Li *et al.*, 2025), with its dynamic and interaction-dependent nature receiving little empirical scrutiny. Third, the boundary conditions governing ELM's peripheral route remain empirically unexplored in live-streaming, leaving a key theoretical prediction unverified.

Thus, this study employs dual-process theory, distinguishing between central and peripheral routes, to juxtapose CSI and CCI pathways, reconceptualizes expertise as a dynamic, interaction-validated signal, and introduces price sensitivity as a moderating variable to probe the boundary conditions of peripheral-route persuasion.

2.2 Consumer trust

Existing research has approached trust formation from three perspectives: streamer characteristics, encompassing professional competence and attractiveness (Alnoor *et al.*, 2024); interactive process, wherein real-time interaction bolsters social presence (Fu *et al.*, 2024); and social influence, operationalized through peer interactions and social validation (Zhang *et al.*, 2022). Recent studies have further extended this line to trust transfer mechanisms (Li *et al.*, 2025) and their boundary conditions (Li *et al.*, 2024).

However, these studies have not distinguished the pathways through which trust is constructed. According to ELM, trust generated through the central and peripheral routes may structurally diverge in both its cognitive architecture and longevity (Petty and Cacioppo, 1986). Therefore, this study introduces price sensitivity as a moderator to identify when peripheral-route trust formation occurs, providing empirical evidence for the model's boundary conditions.

2.3 Theoretical foundation: integrating UGT and ELM

This study integrates UGT and ELM to distinguish the cognitive routes activated by different interaction types. UGT captures consumers' informational, social, and hedonic motivations for live-streaming shopping, while ELM explains how these gratifications translate into trust via central or peripheral routes (Table 1).

In live-streaming, informational gratification triggers the central route, prompting systematic evaluation of streamer expertise and responsiveness, whereas social and hedonic gratifications activate the peripheral route, relying on heuristic cues such as social proof and affect transfer. Grounded in signaling theory (Spence, 1973), expertise is reconceived as a dynamic signal whose credibility is established and verified through real-time interaction. Both pathways jointly shape consumer trust and purchase intention, with meaningful implications for the persistence of trust formed though distinct cognitive mechanisms.

3. Hypothesis development

Figure 1 presents the proposed theoretical model, illustrating how real-time interaction leads to purchase intention through perceived trust and how price sensitivity moderates this process.

3.1 The influence of CSI

Under the UGT-ELM framework, CSI activates the central route by fulfilling informational needs: expertise provides the cognitive basis of the interactive signal, while responsiveness validates it in real time.

3.1.1 The influence of expertise. Expertise refers to a streamer's ability to recommend products based on professional knowledge and experience, a key dimension of interaction

Table 1. Mapping of UGT onto the ELM

Gratification type	Definition	Interaction dimension	Theoretical link to ELM
Informational	Seeking accurate product information to make well-informed decisions	CSI (expertise and responsiveness)	Central route: information quality triggers systematic processing
Social	Seeking identification and reassurance from similar others	CCI (personalization)	Peripheral route: social proof
Hedonic	Seeking pleasure and immersive experiences	CCI (entertainment)	Peripheral route: affect transfer

Source(s): Authors' own work

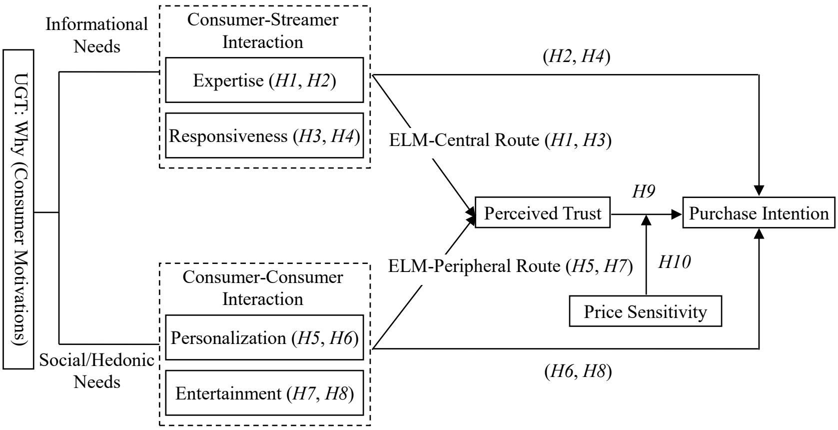

Figure 1. Research framework and hypotheses. Source: Authors' own work

quality (Lu *et al.*, 2024). Through the central route, expertise fosters consumer trust via rational evaluation in two ways. First, it reduces information asymmetry by clarifying product attributes, thereby lowering perceived purchase risk (Wongkitrungrueng and Assarut, 2020). Second, systematic demonstration of professional knowledge encourages parasocial trust, increasing consumer confidence in the streamer and their recommendations (Zhang *et al.*, 2023). This trust deepens consumer immersion and engagement, strengthening CSI and reinforcing perceived expertise in a positive feedback loop (Liao *et al.*, 2023). Moreover, consumers are more receptive to recommendations from competent streamers (Cheah *et al.*, 2024). Based on this, we hypothesize:

H1. Expertise is positively associated with perceived trust.

Additionally, expertise may directly influence purchase intentions by simplifying complex product evaluations and lowering decision-making barriers. Professional demonstrations simplify complex product attributes, enabling more efficient informed decisions, especially for experience and credence goods that are difficult to evaluate prior to purchase (Dang-Van *et al.*, 2023). Thus, we propose:

H2. Expertise is positively associated with purchase intention.

3.1.2 The influence of responsiveness. The real-time question-and-answer nature of live-streaming gives responsiveness its dynamic character (Zhai and Chen, 2023), with instantaneous feedback conveying product value, fostering immersion, and encouraging participation (Gao *et al.*, 2025).

As the real-time interactive manifestation of underlying expertise, responsiveness directly addresses consumers' informational needs. Timely and substantive responses transform static expertise claims into dynamic signals subject to real-time verification, feeding evaluable information into the central route. The credibility of expertise thus hinges on interactive validation.

Responsiveness may build trust through three interrelated pathways. First, it provides immediate product clarification, enhancing information adequacy and consumer understanding, while signaling empathy and a customer-oriented stance (Zhang *et al.*, 2023). Second, minimizing response latency fosters psychological closeness, reducing perceived social distance between consumers and streamers (He *et al.*, 2022). Third, this closeness strengthens perceptions of authenticity and sincerity, reinforcing relational trust (Zhang *et al.*, 2022). Based on this, we hypothesize:

H3. Responsiveness is positively associated with perceived trust.

Responsiveness may also directly influence purchase intention. By capturing attention peaks in real-time interaction, it can trigger impulse mechanisms that convert transient interest into purchase behavior (Gu *et al.*, 2023). Streamers' immediate responses may evoke scarcity or fear of missing out, prompting consumers to bypass deliberative processing and accelerate purchase decisions (Sun *et al.*, 2024). Thus, we propose:

H4. Responsiveness is positively associated with purchase intention.

3.2 The influence of CCI

Under the UGT-ELM framework, CCI activates the peripheral route by fulfilling personalization and entertainment needs, building trust via heuristic cues: social proof and affect transfer.

3.2.1 The influence of personalization. In live-streaming, informed consumers share product-related experiential insights, creating a diversified information flow from which other participants selectively extract content that they perceive as personally relevant (Zhang and Zhang, 2024; Zhang *et al.*, 2024; Zhang and Ruan, 2024).

When consumers observe similar others endorsing a product, they use this social cue to form positive judgment of the product's reliability (Fu *et al.*, 2024). Such a favorable product assessment may then transfer to the streamer, elevating perceptions of the streamer's own trustworthiness (Tripp *et al.*, 2022). Thus, we hypothesize:

H5. Personalization is positively associated with perceived trust.

Personalization may also directly influence purchase intention by enhancing information efficiency. It enables real-time access to customized information (Zhang *et al.*, 2022), reducing cognitive load and decision barriers, shortening decision time (Lv *et al.*, 2022), and increasing receptivity to recommendations (Wang *et al.*, 2024). Personalized filtering may also help consumers evaluate options more effectively and arrive at more informed purchase decisions (Fu *et al.*, 2024). Thus, we propose:

H6. Personalization is positively associated with purchase intention.

3.2.2 The influence of entertainment. Entertainment in live-streaming arises from multidirectional consumer interactions, such as danmaku (Gu *et al.*, 2023). These interactions enable consumers to co-construct socioemotional experiences and foster collective emotional resonance (Mo and Yang, 2026).

Shared entertainment experiences may create a sense of parasocial community, fostering emotional connections with the streamer and perceptions of warmth and authenticity, thereby facilitating trust formation (Kim *et al.*, 2026). Positive emotions may also strengthen consumer bonds and indirectly enhance trust (Hsu and Hu, 2024). Thus, we hypothesize:

H7. Entertainment is positively associated with perceived trust.

Entertainment may also directly influence purchase intention through three pathways. First, via affect transfer, positive emotions generated through interaction may transfer to recommended products, stimulating purchase intention (Yu *et al.*, 2025). Second, via flow experience, interactive entertainment may induce temporal distortion, enhancing purchase intention by deepening information processing and filtering distractions (Wang *et al.*, 2026). Third, via hedonic extension, increased viewing duration and interaction frequency may lead consumers to view products as pleasurable extensions, stimulating desire for possession (Liu *et al.*, 2025). Thus, we propose:

H8. Entertainment is positively associated with purchase intention.

3.3 The influence of perceived trust on purchase intention

In live-streaming, trust reduces information asymmetry and facilitates behavioral conversion, serving as a primary driver of purchase intention (Li *et al.*, 2025). This dual functionality operates via two pathways. Cognitively, it may reduce decision uncertainty (Hameed *et al.*, 2025); affectively, it may elicit emotional commitment and psychological security, thereby facilitating purchase decisions (Alnoor *et al.*, 2024). Thus, we propose:

H9. Perceived trust is positively associated with purchase intention.

3.4 The moderating role of price sensitivity

In live-streaming, where promotions are frequent, price is a core decision-making incentive (Gu *et al.*, 2024). Price sensitivity, defined as consumers' attention to price changes and the weight assigned to price in decisions (Li *et al.*, 2024), has generated two competing views on its moderating role in the trust–purchase intention relationship.

The trust signal attenuation hypothesis posits that high price sensitivity activates systematic processing, prompting attribute-based comparisons and price calculations, thereby weakening trust's diagnostic value and its positive effect on purchase intention (Pavlou *et al.*, 2007).

Conversely, the risk-mitigation hypothesis suggests that highly price-sensitive consumers, concerned about potential losses, may rely more on trust as a risk-mitigating mechanism (Mayer *et al.*, 1995).

Given the abundant real-time information available through live-streaming interaction (Huang *et al.*, 2024), price-sensitive consumers tend to adopt attribute-based evaluation strategies. Accordingly, we support the trust signal attenuation hypothesis and propose:

H10. Price sensitivity negatively moderates the relationship between perceived trust and purchase intention.

4. Research methodology

4.1 Measurement

The measurement scales were adapted from validated scales in the literature to suit the live-streaming context. The English items were translated into Chinese using a back-translation procedure. Further, two bilingual researchers verified the translation to ensure item consistency and clarity (Lu *et al.*, 2024).

Specifically, expertise (Li *et al.*, 2025), personalization (Kang *et al.*, 2021), responsiveness (Ma *et al.*, 2024), entertainment (Joo and Yang, 2023), perceived trust (Cheah *et al.*, 2024), price sensitivity (Gu *et al.*, 2024), and purchase intention (Fu *et al.*, 2024) were each measured using a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). Demographic control variables included gender, age, education level, and monthly consumption expenditure (Table 2).

4.2 Data collection and sample

The survey targeted consumers who had watched and purchased through live-streaming. A pilot test with 52 respondents led to the revisions of several measurement items. The main survey was administered via the WJX platform (www.wjx.cn), a national panel of over 2.6 million registered users with demographic quotas. A screening question ("Do you frequently watch live-streaming?") identified eligible respondents; only those who answered "Yes" proceeded. From March 3 to 31, 2025, 532 responses were collected. After excluding incomplete, straight-lined, and overly fast responses (<90 seconds), 409 valid responses remained (valid response rate = 76.9%). The sample size exceeded the minimum requirement for Partial Least Squares Structural Equation Modeling (PLS-SEM), providing sufficient statistical power (Kock and Hadaya, 2018).

The sample was roughly balanced by gender (50.3% male, 49.7% female). The age distribution was dominated by the 21–30 group (49.3%), with 89.6% of respondents aged 41 or under, closely matching the core post-90s consumer demographic. Bachelor's degree holders comprised 46.4%, and enterprise employees represented the largest occupational group (45.7%), both consistent with the live-streaming shopping user profile. Monthly consumption was most concentrated in the ¥1,001–2,000 range (30.0%), with a sample mean of ¥1,846—approximating the national average of ¥1,720 (iResearch, 2025). Relative to industry benchmarks, the sample shows strong representativeness (Table 3).

4.3 Common method bias (CMB)

To control for CMB, this study incorporated a common method factor into the PLS-SEM model (Podsakoff *et al.*, 2024); results are reported in Table 4. The analysis indicates that method variance accounted for only 0.2% of total variance, yielding a substantive-to-method variance ratio of 341:1. Furthermore, none of the 25 method factor loadings reached statistical significance, suggesting that common method bias does not materially affect the study's findings.

Table 2. Constructs and measurement items

Variables	Codes	Measurement item	References
Expertise(Ex)	Ex1	I think the streamer has rich product expertise	Li *et al.* (2025)
	Ex2	I think the streamer can make good use of this product	
	Ex3	I think the streamer knows a lot about the product	
	Ex4	The streamer shows deep, hands-on expertise with the product	
Responsiveness (Re)	Re1	I think the streamer actively responds to consumer questions or topics	Ma *et al.* (2024)
	Re2	The streamer responds to questions thoughtfully, not dismissively	
	Re3	The advice is tailored to the individual	
Personalization(Pe)	Pe1	Sharing the moment with other consumers amplified my interest	Kang *et al.* (2021)
	Pe2	Shared danmaku perspectives reaffirmed my fit with this stream	
	Pe3	The danmaku took the discussion deeper into key issues than I could by myself	
Entertainment(En)	En1	The real-time connection with other consumers via danmaku was very enjoyable	Joo and Yang (2023)
	En2	I lost myself in the stream and the chat, completely losing track of time	
	En3	I found livestream consumer interactions intrinsically motivating	
Perceived Trust (PT)	PT1	I believe the streamer is honest with the consumers	Cheah *et al.* (2024)
	PT2	I trust that the recommendations come from the streamer's genuine experience	
	PT3	I believe that the product information provided by the streamer is truthful	
	PT4	I believe that the seller's conduct will align with the streamer's commitments	
Price Sensitivity (PS)	PS1	I pay more attention to the price of the product when watching the live streaming	Gu *et al.* (2024)
	PS2	I'd be reluctant to buy a product that requires an extra fee at the streamer's studio	
	PS3	I'd hesitate to buy if I'm paying a premium for the stream experience	
Purchase Intention (PI)	PI1	I plan to keep watching the live streaming and consider buying later	Fu *et al.* (2024)
	PI2	I plan to shop regularly at this streamer's studio going forward	
	PI3	I would like to recommend this streamer's studio to others	
	PI4	I follow streamers to better understand products and guide my future purchases	
	PI5	I'll go to this streamer's studio first for similar needs	

Source(s): Authors' own work

5. Data analysis and results

Smart PLS 4 was used for PLS-SEM analysis. Variance inflation factor (VIF) diagnostics (Table 5) shows that all VIF values fell below the threshold of 5 (range: 1.434–2.241), indicating no serious multicollinearity concerns (Liang *et al.*, 2007).

5.1 Assessment of construct measurements

5.1.1 Assessment of scale reliability. Reliability analysis (Table 5) shows that Cronbach's alpha and composite reliability values for all variables exceed 0.700 (Cheung *et al.*, 2023), confirming satisfactory internal consistency reliability.

Table 3. Distribution of sample characteristics

Variables	Options	Frequency	Percentage (%)
Gender	Male	206	50.30
	Female	203	49.70
Age	16–20 years old	76	18.60
	21–30 years old	202	49.30
	31–40 years old	89	21.70
	41–50 years old	25	6.10
	Over 51 years old	17	4.10
Education	High school and below	53	12.90
	Associate degree	117	28.60
	Bachelor's degree	190	46.4
	Master's degree	29	7.0
	PhD	20	4.80
Occupation	School student	84	20.50
	Government/public institution staff	69	16.80
	Enterprise employee	187	45.70
	Self-employed person	47	11.40
	Others	22	5.30
Monthly consumption (¥)	Less than 1000	87	21.20
	1001–2000	123	30.0
	2001–4000	115	28.10
	4001–6000	49	11.90
	More than 6001	35	8.50

Source(s): Authors' own work

5.1.2 Assessment of the convergent validity. Convergent validity analysis (Table 5) shows that all indicator loadings exceeded 0.700 and were statistically significant ($t > 1.96$, $p < 0.05$) (Cheung *et al.*, 2023), and the average variance extracted (AVE) for each construct exceeded 0.50 (Fu *et al.*, 2024), demonstrating good convergent validity. Content validity was established by consulting experts and practitioners during the scale-development phase.

5.1.3 Assessment of discriminant validity. Discriminant validity analysis (Table 6) shows that the square root of each construct's AVE exceeded its highest correlation with any other construct, thereby demonstrating satisfactory discriminant validity (Fu *et al.*, 2024).

5.2 Structural model

The theoretical framework and hypotheses were assessed using a PLS-SEM model built in Smart PLS 4 (Figure 1). Model fit was acceptable (SRMR = 0.05, below 0.08; Liang *et al.*, 2007).

5.2.1 Direct effects test. The direct effects of the four interaction dimensions on perceived trust and purchase intention (H1-H8) were tested using 5,000 bootstrap resamples (Table 7).

Ex positively affected perceived trust (H1: $\beta = 0.158$, $p < 0.01$) and PI (H2: $\beta = 0.246$, $p < 0.001$). Re positively affected PT (H3: $\beta = 0.208$, $p < 0.001$) and PI (H4: $\beta = 0.162$, $p < 0.01$). Pe positively affected PT (H5: $\beta = 0.247$, $p < 0.001$) and PI (H6: $\beta = 0.111$, $p < 0.05$). En positively affected PT (H7: $\beta = 0.128$, $p < 0.05$) and PI (H8: $\beta = 0.252$, $p < 0.001$). In addition, PT positively affected PI (H9: $\beta = 0.15$, $p < 0.01$). All hypotheses received support.

5.2.2 Moderating effect of price sensitivity. In the base mediation model, Pe had a significant direct effect on PI. After introducing PS and its interaction term with PT, however, the direct effect of Pe became non-significant ($\beta = 0.060$, $p = 0.268$, 95% CI [–0.046, 0.166]), whereas the PT × PS interaction was significant (H10: $\beta = -0.088$, $p < 0.05$, 95% CI [–0.168, -0.008]). This finding supports the trust signal attenuation hypothesis: when price-sensitive consumers have access to abundant real-time information, they tend to adopt attribute-based evaluation rather than rely on trust. The results are illustrated in Figure 2.

Table 4. Common method bias analysis

Construct	Indictor	Substantive factor loading ($R1$)	$R1^2$	Method factor loading ($R2$)	$R2^2$
	Ex1	0.862***	0.743	0.004	0.000016
Ex	Ex2	0.841***	0.707	−0.076	0.005776
	Ex3	0.841***	0.707	0.063	0.003969
	Ex4	0.856***	0.733	0.008	0.000064
	R1	0.849***	0.721	−0.016	0.000256
Re	R2	0.866***	0.750	0.026	0.000676
	R3	0.854***	0.729	−0.01	0.0001
	Pe1	0.849***	0.721	−0.016	0.000256
Pe	Pe2	0.853***	0.728	0.026	0.000676
	Pe3	0.850***	0.723	−0.011	0.000121
	En1	0.846***	0.716	−0.049	0.002401
En	En2	0.859***	0.738	0.057	0.003249
	En3	0.838***	0.702	−0.01	0.0001
	PT1	0.844***	0.712	0.07	0.0049
PT	PT2	0.781***	0.610	−0.049	0.002401
	PT3	0.821***	0.674	−0.02	0.0004
	PT4	0.820***	0.672	−0.007	0.000049
	PS1	0.824***	0.679	−0.051	0.002601
PS	PS2	0.833***	0.694	−0.01	0.0001
	PS3	0.794***	0.630	0.064	0.004096
	PI1	0.785***	0.616	−0.022	0.000484
	PI2	0.765***	0.585	−0.075	0.005625
PI	PI3	0.803***	0.645	0.035	0.001225
	PI4	0.788***	0.621	−0.043	0.001849
	PI5	0.825***	0.681	0.096	0.009216
Average		0.830	0.690	−0.00064	0.002024

Note(s): ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$
Source(s): Authors' own work

5.2.3 Mediating effects test. The mediating role of PT was tested using SPSS PROCESS (Model 4) with 5,000 bootstrap resamples and 95% bias-corrected confidence intervals.

As shown in Table 8, all four dimensions exerted significant partial mediating effects on PI through PT. Partial mediation was confirmed for Ex (indirect effect = 0.091, 95% CI [0.051, 0.138]; direct effect = 0.352, 95% CI [0.281, 0.423]), Pe (indirect effect = 0.111, 95% CI [0.070, 0.160]; direct effect = 0.256, 95% CI [0.180, 0.333]), En (indirect effect = 0.090, 95% CI [0.053, 0.132]; direct effect = 0.370, 95% CI [0.298, 0.441]), and Re (indirect effect = 0.105, 95% CI [0.065, 0.152]; direct effect = 0.236, 95% CI [0.160, 0.312]).

Conditional indirect effect analyses (Table 8) further show that the indirect effects varied across PS levels. At low PS, the conditional indirect effects of Re (0.042, 95% CI [0.008, 0.079]) and Pe (0.050, 95% CI [0.010, 0.093]) were significant. At high PS, neither effect was significant. In contrast, Ex (low PS: 0.032, 95% CI [−0.001, 0.068]; high PS: 0.004, 95% CI [−0.019, 0.028]) and En (low PS: 0.026, 95% CI [−0.006, 0.060]; high PS: 0.003, 95% CI [−0.019, 0.027]) did not exhibit significant conditional indirect effects at either price sensitivity level.

These results indicate that PS moderates the indirect effects of Re and Pe which are significant only for consumers with low PS. By contrast, the indirect effects of Ex and En on purchase intention are independent of PS.

5.2.4 Coefficient comparison tests. Significant differences in the path coefficients of the interaction dimensions were tested using Smart PLS's model constraint function (Sarstedt *et al.*, 2020); results are reported in Table 9. The effects of the dimensions were not statistically distinguishable. As presented in Table 9, none of the twelve pairwise comparisons for the paths to trust and purchase intention reached statistical significance. The 95% confidence intervals

Table 5. Reliability and validity analysis

Construct	Items	Factor loading	VIF	Cronbach's α	CR	AVE
Ex	Ex1	0.863	2.241	0.872	0.874	0.723
	Ex2	0.833	2.049			
	Ex3	0.847	2.026			
	Ex4	0.858	2.177			
Re	R1	0.847	1.777	0.818	0.821	0.733
	R2	0.859	1.903			
	R3	0.863	1.796			
Pe	Pe1	0.846	1.751	0.809	0.809	0.724
	Pe2	0.853	1.779			
	Pe3	0.852	1.756			
En	En1	0.835	1.743	0.804	0.807	0.718
	En2	0.863	1.808			
	En3	0.844	1.669			
PT	PT1	0.855	1.973	0.834	0.842	0.667
	PT2	0.77	1.623			
	PT3	0.82	1.820			
	PT4	0.82	1.820			
PS	PS1	0.827	1.537	0.751	0.755	0.668
	PS2	0.839	1.571			
	PS3	0.786	1.434			
PI	PI1	0.783	1.758	0.853	0.856	0.630
	PI2	0.761	1.675			
	PI3	0.806	1.873			
	PI4	0.785	1.769			
	PI5	0.831	1.994			

Source(s): Authors' own work

Table 6. Discrimination validity analysis

Fornell–Larcker criterion	En	Ex	PI	PS	PT	Pe	Re
En	*0.847*						
Ex	0.533	*0.850*					
PI	0.550	0.533	*0.794*				
PS	−0.427	−0.474	−0.567	*0.817*			
PT	0.398	0.391	0.453	−0.500	*0.817*		
Pe	0.466	0.434	0.442	−0.461	0.430	*0.851*	
Re	0.343	0.280	0.401	−0.395	0.362	0.266	*0.856*

Source(s): Authors' own work

for all pairwise differences included zero, indicating that the effects of the four interaction dimensions were not statistically distinguishable.

6. Discussion and implications

6.1 Key findings

This study supports a dual-process framework in which real-time interaction influences purchase intention through perceived trust, moderated by price sensitivity (Table 10).

First, this study demonstrates that comparable effect sizes do not inherently imply equivalent mechanisms. All four dimensions were similarly associated with perceived trust and purchase intention. However, under conditions of price sensitivity moderation, only

Table 7. Results of structural model assessment

Path	Basic mediation model *t*-value	Path coefficient (β)	Result	Moderated mediation model *t*-value	Path coefficient (β)	Result
En → PI	3.803	0.252***	Supported	3.468	0.222***	Supported
En → PT	1.999	0.128*	Supported	1.999	0.128*	Supported
Ex → PI	4.021	0.246***	Supported	2.873	0.170**	Supported
Ex → PT	2.64	0.158**	Supported	2.64	0.158**	Supported
Pe → PI	2.005	0.111*	Supported	1.107	0.06^{ns}	Not Supported
Pe → PT	4.249	0.247***	Supported	4.249	0.247***	Supported
PT → PI	2.632	0.150**	Supported	1.981	0.150*	Supported
Re → PI	2.95	0.162**	Supported	2.105	0.114*	Supported
Re → PT	3.89	0.208***	Supported	3.891	0.208***	Supported
PS → PI				5.25	0.294***	Supported
PS × PT → PI				2.167	0.088*	Supported

Note(s): ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$
Source(s): Authors' own work

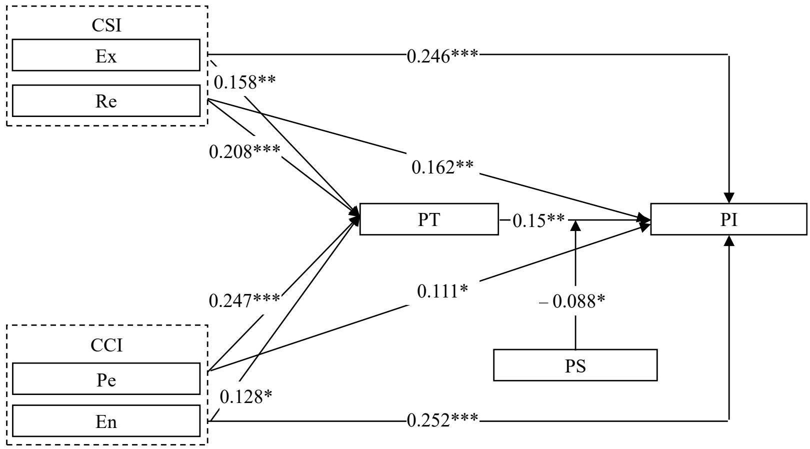

Figure 2. Results of path analysis. Note: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Source: Authors' own work

personalization's direct association became non-significant, suggesting that statistically indistinguishable effects may operate through different mechanisms.

Second, perceived trust acts as a partial mediator, exhibiting conditional patterns highly consistent with ELM. Central-route variables differ in trust mediation (responsiveness conditional, expertise stable), whereas peripheral-route variables diverge: personalization operates via trust only under low motivation, while entertainment primarily through direct pathways.

Third, price sensitivity negatively moderates the trust–purchase intention relationship. Heightened price sensitivity appears to trigger more systematic cognitive processing, shifting consumers to favor attribute-based comparisons and reducing their reliance on trust as a peripheral heuristic cue. Consequently, the positive association between trust and purchase intention weakens as price sensitivity rises.

6.2 Theoretical contributions

First, this study contributes to marketing theory by challenging the implicit assumption in prior research that similar effect sizes reflect comparable underlying mechanisms (Luo *et al.*, 2024b). While conventional literature treats matching path coefficients as evidence of a uniform persuasion process, the conditional evidence here suggests that statistically

Table 8. Mediating effects and conditional indirect effects of interaction dimensions

Path	Effect	95% CI	Results	PS level	Effect	SE	95% CI	Results
Ex → PT → PI	0.091	[0.051, 0.138]	Partial mediated	Low	0.032	0.018	[−0.001, 0.068]	Not significant
				High	0.004	0.012	[−0.019, 0.028]	Not significant
Re → PT → PI	0.105	[0.065, 0.152]	Partial mediated	Low	0.042	0.018	[0.008, 0.079]	Significant
				High	0.005	0.013	[−0.021, 0.031]	Not significant
Pe → PT → PI	0.111	[0.070, 0.160]	Partial mediated	Low	0.050	0.021	[0.010, 0.093]	Significant
				High	0.006	0.017	[−0.027, 0.041]	Not significant
En → PT → PI	0.090	[0.053, 0.132]	Partial mediated	Low	0.026	0.017	[−0.006, 0.060]	Not significant
				High	0.003	0.012	[−0.019, 0.027]	Not significant

Note(s): Conditional indirect effects evaluated at low (−1 SD) and high (+1 SD) levels of price sensitivity
Source(s): Authors' own work

Table 9. Coefficient comparison tests for interaction dimensions

Pairwise comparisons	Δβ	*t*	*p*	95% CI	Δβ	*t*	*p*	95% CI
Effects on PT					Effects on PI			
Ex vs. Pe	0.089	1.067	0.286	[−0.252, 0.074]	0.110	1.375	0.169	[−0.047, 0.267]
Ex vs. En	0.030	0.342	0.732	[−0.142, 0.202]	0.052	0.596	0.551	[−0.223, 0.119]
Ex vs. Re	0.050	0.620	0.535	[−0.208, 0.108]	0.056	0.700	0.484	[−0.101, 0.213]
Pe vs. En	0.119	1.377	0.168	[−0.050, 0.288]	0.162	1.935	0.053	[−0.326, 0.002]
Pe vs. Re	0.039	0.492	0.623	[−0.116, 0.194]	0.054	0.705	0.481	[−0.204, 0.096]
En vs. Re	0.080	0.956	0.339	[−0.244, 0.084]	0.108	1.287	0.197	[−0.056, 0.272]

Source(s): Authors' own work

Table 10. Summary of the CSI-CCI dual-process framework

Core insight	Description	Empirical evidence
Effect size ≠ mechanism	While statistically indistinguishable, Pe's direct effect dissipates upon controlling for PS, whereas the other dimensions remain robust	Pe → PI: 0.111* → 0.060 (n.s.) Ex → PI: 0.246*** → 0.170** R → PI: 0.162** → 0.114* En → PI: 0.252*** → 0.222***
Same trust, different routes	CSI builds trust via the central route, while CCI builds trust via the peripheral route	CSI→PT: 0.158** / 0.208*** CCI→ PT: 0.247*** / 0.128*
PS as a boundary condition	PS negatively moderates the PT–PI relationship. High PS triggers systematic processing, thereby reducing reliance on PT as a peripheral heuristic	PT× PS → PI: β = −0.088* Pe indirect effect: 0.050* [0.010, 0.093] (low PS), n.s. (high PS)

Note(s): ****p* < 0.001, ***p* < 0.01, **p* < 0.05
Source(s): Authors' own work

indistinguishable effects can operate through entirely different mechanisms. Specifically, surface-level statistical symmetry does not guarantee a shared psychological route to purchase intention when environmental boundaries like price sensitivity are introduced.

Second, extending the static view of streamer expertise (Li *et al.*, 2025) and drawing on signaling theory (Spence, 1973), this study reconceptualizes expertise as a dynamic signal that must be validated through live interaction. In doing so, the findings demonstrate that real-time responsiveness functions as an independent, parallel pillar in trust formation, alongside established expertise.

Third, this study empirically tests the boundary conditions of the peripheral-route persuasion within live-streaming. Personalization's indirect effect via trust is exclusively significant under low-price-sensitivity consumers, and price sensitivity attenuates the direct trust–purchase intention relationship. These findings provide robust empirical backing for ELM's foundational premise that peripheral-route persuasion requires low processing motivation (Petty and Cacioppo, 1986), thereby extending understanding of the peripheral route's boundary conditions in live-streaming.

6.3 Managerial implications

First, achieving operational success in live-streaming depends on systematic selection of interaction dimensions, which platform managers must tailor to both product classification and strategic goals. Expertise yields are most effective for technically complex products that require cognitive evaluation. Real-time responsiveness functions as a robust driver of consumer trust and purchase intention, meriting priority investment. Entertainment is conversion-focused, with most of its effect bypassing the trust, and is best deployed in mid-to-late live-streaming stages to reduce decision fatigue and encourage impulse purchases.

Second, practitioners should deploy price sensitivity as a basis for customer segmentation. Among high price-sensitive segments, value-oriented signals such as competitive pricing and quality assurance should be prioritized over personalized social proof, since personalization's direct effect on purchase intention diminishes under conditions of heightened price consciousness. In contrast, for low-sensitivity segments, personalization should be harnessed to build trust, danmaku interactions encouraged to foster community, and entertainment value mobilized as a conversion mechanism.

Third, expertise should be validated through dynamic real-time interaction. Platforms should implement streamer training protocols that place particular emphasis on delivering thorough and substantive responses to consumer questions. Encouraging viewers to challenge streamers with rigorous questions allow abstract claims of professional knowledge to be publicly verified, effectively converting them into observable and credible trust signals. Finally, platforms should strengthen responsiveness infrastructure, including adequate peak-hour staffing and resource allocation, so that timely and comprehensive replies can be consistently delivered, treating responsiveness as a trust-building force rather than a secondary complement to expertise.

6.4 Limitations and future research

First, a tension exists between the process-oriented framework and the cross-sectional data. The model posits that different interaction types build trust via distinct pathways, which may yield trust with different durability and resistance to counter-persuasion. However, cross-sectional data cannot capture trust's dynamic evolution or test such pathway differences (He *et al.*, 2026). Future research could address this using longitudinal designs or trust-violation experiments.

Second, concerns about single-source bias and common method variance persist. Despite procedural and statistical controls, shared variance may still influence the results. Additionally, measuring purchase intention rather than actual behavior leaves an intention–behavior gap. Future research could enhance robustness by incorporating platform-generated behavioral data (Mo and Yang, 2026), multiple secondary sources, and multi-method triangulation.

Third, other boundary conditions beyond price sensitivity merit exploration. Streamer type is a promising candidate: influencer streamers likely provide peripheral cues, while expert streamers may elicit central-route processing (Zheng *et al.*, 2026). Future research should test the generalizability of these pathway effects across different streamer types.

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References

Alnoor, A., Abbas, S., Khaw, K.W., Muhsen, Y.R. and Chew, X. (2024), "Unveiling the optimal configuration of impulsive buying behavior using fuzzy set qualitative comparative analysis and multi-criteria decision approach", *Journal of Retailing and Consumer Services*, Vol. 81, 104057, doi: 10.1016/j.jretconser.2024.104057.

Cheah, C.W., Koay, K.Y. and Lim, W.M. (2024), "Social media influencer over-endorsement: implications from a moderated-mediation analysis", *Journal of Retailing and Consumer Services*, Vol. 79, 103831, doi: 10.1016/j.jretconser.2024.103831.

Chen, A., Zhang, Y., Liu, Y. and Lu, Y. (2023), "Be a good speaker in livestream shopping: a speech act theory perspective", *Electronic Commerce Research and Applications*, Vol. 61, 101301, doi: 10.1016/j.elerap.2023.101301.

Chen, X., Wang, Y., Wei, S. and Shen, J. (2025), "The effect of herd behavior on consumer intention in live streaming e-commerce: the moderating role of interaction", *International Journal of Human-Computer Interaction*, Vol. 41 No. 2, pp. 1674-1687, doi: 10.1080/10447318.2024.2364464.

Cheung, G.W., Cooper-Thomas, H.D., Lau, R.S. and Wang, L.C. (2023), "Reporting reliability, convergent and discriminant validity with structural equation modeling: a review and best-practice recommendations", *Asia Pacific Journal of Management*, Vol. 41 No. 2, pp. 745-783, doi: 10.1007/s10490-023-09871-y.

China Internet Network Information Center (2025), "The 56th statistical report on China's internet development", available at: https://www.cnnic.org.cn/n4/2025/0721/c88-11328.html.pdf (accessed 21 July 2025).

Dang-Van, T., Vo-Thanh, T., Vu, T.T., Wang, J. and Nguyen, N. (2023), "Do consumers stick with good-looking broadcasters? The mediating and moderating mechanisms of motivation and emotion", *Journal of Business Research*, Vol. 156, 113483, doi: 10.1016/j.jbusres.2022.113483.

Fan, X., Zhang, L., Guo, X. and Zhao, W. (2024), "The impact of live-streaming interactivity on live-streaming sales mode based on game-theoretic analysis", *Journal of Retailing and Consumer Services*, Vol. 81, 103981, doi: 10.1016/j.jretconser.2024.103981.

Fu, S., Zheng, X., Hou, T. and Yang, Y. (2024), "Product purchase or gift-giving? An investigation of different viewer-streamer interaction strategies in tourism live streaming", *Tourism Management Perspectives*, Vol. 51, 101219, doi: 10.1016/j.tmp.2024.101219.

Gao, J., Zhao, X., Zhai, M., Zhang, D. and Li, G. (2025), "AI or human? The effect of streamer types on consumer purchase intention in live streaming", *International Journal of Human-Computer Interaction*, Vol. 41 No. 1, pp. 305-317, doi: 10.1080/10447318.2023.2299900.

Gu, Y., Cheng, X. and Shen, J. (2023), "Design shopping as an experience: exploring the effect of the live-streaming shopping characteristics on consumers' participation intention and memorable experience", *Information and Management*, Vol. 60 No. 5, 103810, doi: 10.1016/j.im.2023.103810.

Gu, X., Zhang, X. and Kannan, P.K. (2024), "Influencer mix strategies in livestream commerce: impact on product sales", *Journal of Marketing*, Vol. 88 No. 4, pp. 64-83, doi: 10.1177/00222429231213581.

Guo, Y., Zhang, K. and Wang, C. (2022), “Way to success: understanding top streamer’s popularity and influence from the perspective of source characteristics”, *Journal of Retailing and Consumer Services*, Vol. 64, 102786, doi: 10.1016/j.jretconser.2021.102786.

Hameed, I., Zainab, B., Akram, U., Ying, W.J., Xing, C.C. and Khan, K. (2025), “Decoding willingness to buy in live-streaming retail: the application of stimulus organism response model using PLS-SEM and SEM-ANN”, *Journal of Retailing and Consumer Services*, Vol. 84, 104236, doi: 10.1016/j.jretconser.2025.104236.

Hao, S. and Huang, L. (2025), “The persuasive effects of scarcity messages on impulsive buying in live-streaming e-commerce: the moderating role of time scarcity”, *Asia Pacific Journal of Marketing and Logistics*, Vol. 37 No. 2, pp. 441-459, doi: 10.1108/APJML-03-2024-0269.

He, Y., Li, W. and Xue, J. (2022), “What and how driving consumer engagement and purchase intention in officer live streaming? A two-factor theory perspective”, *Electronic Commerce Research and Applications*, Vol. 56, 101223, doi: 10.1016/j.elerap.2022.101223.

He, L., Li, X., Li, Y., Liu, Y., Zhang, N. and Zhou, X. (2026), “Is more always better? The effect of audience size on sales performance in live streaming commerce: a multimethod study”, *Journal of Retailing and Consumer Services*, Vol. 89, 104613, doi: 10.1016/j.jretconser.2025.104613.

Hsu, L.C. and Hu, S.Y. (2024), “Antecedents and consequences of the trust transfer effect on social commerce: the moderating role of customer engagement”, *Current Psychology*, Vol. 43 No. 5, pp. 4040-4061, doi: 10.1007/s12144-023-04634-w.

Huang, W., Jiang, W., Luo, X., Mei, X. and Wei, L. (2024), “It’s showtime: live-streaming e-commerce and optimal promotion insertion policy”, *Production and Operations Management*, Vol. 35 No. 2, pp. 434-450, doi: 10.1177/10591478231224975.

iResearch (2025), “Analysis and trend research report on the operation of China’s live e-commerce industry from 2025-2029”, available at: https://report.iimedia.cn/repo100-0/57811.html (accessed 2 June 2025).

Joo, E. and Yang, J. (2023), “How perceived interactivity affects consumers’ shopping intentions in live stream commerce: roles of immersion, user gratification and product involvement”, *The Journal of Research in Indian Medicine*, Vol. 17 No. 5, pp. 754-772, doi: 10.1108/JRIM-02-2022-0037.

Kang, K., Lu, J., Guo, L. and Li, W. (2021), “The dynamic effect of interactivity on customer engagement behavior through tie strength: evidence from live streaming commerce platforms”, *International Journal of Information Management*, Vol. 56, 102251, doi: 10.1016/j.ijinfomgt.2020.102251.

Kim, H.S., Chung, M.Y. and Kim, Y. (2026), “Exploring the role of user participation in emotional contagion and coping in cancer vlog communities on YouTube”, *Health Communication*, Vol. 41 No. 4, pp. 517-530, doi: 10.1080/10410236.2025.2520512.

Kock, N. and Hadaya, P. (2018), “Minimum sample size estimation in PLS-SEM: the inverse square root and gamma-exponential methods”, *Information Systems Journal*, Vol. 28 No. 1, pp. 227-261, doi: 10.1111/isj.12131.

Li, Y., Ning, Y., Fan, W., Kumar, A. and Ye, F. (2024), “Channel choice in live streaming commerce”, *Production and Operations Management*, Vol. 33 No. 11, pp. 2221-2240, doi: 10.1177/10591478241270118.

Li, X., Wang, Q., Yao, X., Yan, X. and Li, R. (2025), “How do influencers’ impression management tactics affect purchase intention in live commerce?-Trust transfer and gender differences”, *Information and Management*, Vol. 62 No. 2, 104094, doi: 10.1016/j.im.2024.104094.

Liang, H., Saraf, N., Hu, Q. and Xue, Y. (2007), “Assimilation of enterprise systems: the effect of institutional pressures and the mediating role of top management”, *MIS Quarterly*, Vol. 31 No. 1, pp. 59-87, doi: 10.2307/25148781.

Liao, J., Chen, K., Qi, J., Li, J. and Yu, I.Y. (2023), “Creating immersive and parasocial live shopping experience for viewers: the role of streamers’ interactional communication style”, *The Journal of Research in Indian Medicine*, Vol. 17 No. 1, pp. 140-155, doi: 10.1108/JRIM-04-2021-0114.

Liu, Q., Ma, N. and Zhang, X. (2025), "Can AI-virtual anchors replace human internet celebrities for live streaming sales of products? An emotion theory perspective", *Journal of Retailing and Consumer Services*, Vol. 82, 104107, doi: 10.1016/j.jretconser.2024.104107.

Lu, H.H., Chen, C.F. and Tai, Y.W. (2024), "Exploring the roles of vlogger characteristics and video attributes on followers' value perceptions and behavioral intention", *Journal of Retailing and Consumer Services*, Vol. 77, 103686, doi: 10.1016/j.jretconser.2023.103686.

Luo, X., Cheah, J.H., Hollebeek, L.D. and Lim, X.J. (2024a), "Boosting customers' impulsive buying tendency in live-streaming commerce: the role of customer engagement and deal proneness", *Journal of Retailing and Consumer Services*, Vol. 77, 103644, doi: 10.1016/j.jretconser.2023.103644.

Luo, L., Xu, M. and Zheng, Y. (2024b), "Informative or affective? Exploring the effects of streamers' topic types on user engagement in live streaming commerce", *Journal of Retailing and Consumer Services*, Vol. 79, 103799, doi: 10.1016/j.jretconser.2024.103799.

Lv, X., Zhang, R., Su, Y. and Yang, Y. (2022), "Exploring how live streaming affects immediate buying behavior and continuous watching intention: a multigroup analysis", *Journal of Travel and Tourism Marketing*, Vol. 39 No. 1, pp. 109-135, doi: 10.1080/10548408.2022.2052227.

Ma, X., Aw, E.C.X. and Filieri, R. (2024), "From screen to cart: how influencers drive impulsive buying in livestreaming commerce", *The Journal of Research in Indian Medicine*, Vol. 18 No. 6, pp. 1034-1058, doi: 10.1108/JRIM-05-2023-0142.

Mayer, R.C., Davis, J.H. and Schoorman, F.D. (1995), "An integrative model of organizational trust", *Academy of Management Review*, Vol. 20 No. 3, pp. 709-734, doi: 10.5465/amr.1995.9508080335.

Mo, S. and Yang, Y. (2026), "The effect of cross-gender endorsement in live streaming: the moderating role of sexually related products", *Journal of Retailing and Consumer Services*, Vol. 90, 104676, doi: 10.1016/j.jretconser.2025.104676.

Park, H.J. and Lin, L.M. (2020), "The effects of match-ups on the consumer attitudes toward internet celebrities and their live streaming contents in the context of product endorsement", *Journal of Retailing and Consumer Services*, Vol. 52, 101934, doi: 10.1016/j.jretconser.2019.101934.

Pavlou, P.A., Liang, H. and Xue, Y. (2007), "Understanding and mitigating uncertainty in online exchange relationships: a principal-agent perspective", *MIS Quarterly*, Vol. 31 No. 1, pp. 105-136, doi: 10.2307/25148783.

Petty, R. and Cacioppo, J. (1986), "The elaboration likelihood model of persuasion", in Petty, R.E. and Cacioppo, J.T. (Eds), *Communication and Persuasion: Central and Peripheral Routes to Attitude Change*, Springer, pp. 1-24, doi: 10.1007/978-1-4612-4964-1_1.

Podsakoff, P.M., Podsakoff, N.P., Williams, L.J., Huang, C. and Yang, J. (2024), "Common method bias: it's bad, it's complex, it's widespread, and it's not easy to fix", *Annual Review of Organizational Psychology and Organizational Behavior*, Vol. 11 No. 1, pp. 17-61, doi: 10.1146/annurev-orgpsych-110721-040030.

Sarstedt, M., Hair, J.F., Nitzl, C., Ringle, C.M. and Howard, M.C. (2020), "Beyond a tandem analysis of SEM and PROCESS: use of PLS-SEM for mediation analyses", *International Journal of Market Research*, Vol. 62 No. 3, pp. 288-299, doi: 10.1177/1470785320915686.

Spence, M. (1973), "Job market signaling", *Quarterly Journal of Economics*, Vol. 87 No. 3, pp. 355-374, doi: 10.2307/1882010.

State Administration for Market Regulation Development Research Center and Chinese Academy of Social Sciences (2026), "2025 live streaming e-commerce industry development white paper", available at: https://www.samr.gov.cn (accessed 9 February 2026).

Sun, J., Sarfraz, M., Ivascu, L., Han, H. and Ozturk, I. (2024), "Live streaming and livelihoods: decoding the creator Economy's influence on consumer attitude and digital behavior", *Journal of Retailing and Consumer Services*, Vol. 78, 103753, doi: 10.1016/j.jretconser.2024.103753.

Tripp, J., McKnight, D.H. and Lankton, N. (2022), "What most influences consumers' intention to use? Different motivation and trust stories for Uber, airbnb, and taskrabbit", *European Journal of Information Systems*, Vol. 32 No. 5, pp. 818-840, doi: 10.1080/0960085X.2022.2062469.

Wang, Q., Li, X. and Yan, X. (2026), "When the mindful ones experience flow: a moderated-mediation model of purchase intention in live commerce", *Information Technology and People*, Vol. 39 No. 2, pp. 635-667, doi: 10.1108/ITP-04-2023-0377.

Wang, Y., Zhu, J., Liu, R. and Jiang, Y. (2024), "Enhancing recommendation acceptance: resolving the personalization-privacy paradox in recommender systems: a privacy calculus perspective", *International Journal of Information Management*, Vol. 76, 102755, doi: 10.1016/j.ijinfomgt.2024.102755.

Wongkitrungrueng, A. and Assarut, N. (2020), "The role of live streaming in building consumer trust and engagement with social commerce sellers", *Journal of Business Research*, Vol. 117, pp. 543-556, doi: 10.1016/j.jbusres.2018.08.032.

Xue, J., Liang, X., Xie, T. and Wang, H. (2020), "See now, act now: how to interact with customers to enhance social commerce engagement?", *Information and Management*, Vol. 57 No. 6, 103324, doi: 10.1016/j.im.2020.103324.

Yu, T., Teoh, A.P., Bian, Q., Liao, J. and Wang, C. (2025), "Can virtual influencers affect purchase intentions in tourism and hospitality e-commerce live streaming? An empirical study in China", *International Journal of Contemporary Hospitality Management*, Vol. 37 No. 1, pp. 216-238, doi: 10.1108/IJCHM-03-2024-0358.

Zhai, M. and Chen, Y. (2023), "How do relational bonds affect user engagement in e-commerce livestreaming? The mediating role of trust", *Journal of Retailing and Consumer Services*, Vol. 71, 103239, doi: 10.1016/j.jretconser.2022.103239.

Zhang, N. and Ruan, C. (2024), "Danmaku consistency reduces consumer purchases during live streaming: a dual-process model", *Psychology and Marketing*, Vol. 41 No. 11, pp. 2591-2607, doi: 10.1002/mar.22074.

Zhang, X. and Zhang, S. (2024), "Investigating impulse purchases in live streaming e-commerce: a perspective of match-ups", *Technological Forecasting and Social Change*, Vol. 205, 123513, doi: 10.1016/j.techfore.2024.123513.

Zhang, M., Liu, Y., Wang, Y. and Zhao, L. (2022), "How to retain customers: understanding the role of trust in live streaming commerce with a socio-technical perspective", *Computers in Human Behavior*, Vol. 127, 107052, doi: 10.1016/j.chb.2021.107052.

Zhang, P., Chao, C.W.F., Chiong, R., Hasan, N., Aljaroodi, H.M. and Tian, F. (2023), "Effects of in-store live stream on consumers' offline purchase intention", *Journal of Retailing and Consumer Services*, Vol. 72, 103262, doi: 10.1016/j.jretconser.2023.103262.

Zhang, Y., Li, K., Qian, C., Li, X. and Yuan, Q. (2024), "How real-time interaction and sentiment influence online sales? Understanding the role of live streaming Danmaku", *Journal of Retailing and Consumer Services*, Vol. 78, 103793, doi: 10.1016/j.jretconser.2024.103793.

Zheng, J., Wang, Y., Dou, Y. and Ling, H. (2026), "The marketing effects of live streaming in online marketplaces", *Information and Management*, Vol. 63 No. 2, 104288, doi: 10.1016/j.im.2025.104288.

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