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Live-Streaming Commerce and Consumer Purchase Intentions: A Trust-Based Analysis

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ABSTRACT
Live-streaming commerce (LSC) has emerged as a dominant online shopping model in China, with influencers-turned-streamers facing the critical challenge of building consumer trust. This study applies the Stimulus-Organism-Response (S-O-R) framework to develop a model explaining how streamers' characteristics shape consumers' purchase intentions. Specifically, it examines consumers' perceptions of streamers across three dimensions: expertise (product knowledge), responsiveness (real-time interaction), and affinity (emotional connection). The model further explores how these dimensions influence consumer purchase intentions, with trust in streamers acting as a mediating factor, and investigates the moderating role of streamer morality in the trust-purchase intention relationship. Using data from 214 valid questionnaires collected via an online survey, the study employs SPSS 26.0 for descriptive analysis and SmartPLS 4.0 for structural equation modeling. Results reveal that all three characteristics significantly enhance consumer trust, which in turn drives purchase intentions. Among these, affinity exerts the strongest influence, highlighting the importance of emotional engagement in LSC. Additionally, streamer morality moderates the trust-purchase intention link, suggesting that higher perceived morality amplifies the positive effect of trust on buying decisions. The study contributes to LSC scholarship by refining the conceptualization of responsiveness, expanding the role of affinity beyond traditional influencer marketing, and integrating morality as a contextual moderator. Practically, it offers actionable insights that influencers should prioritize fostering genuine connections, demonstrating expertise, and maintaining ethical practices. Brands and agencies must vet streamers for both competence and integrity when forming partnerships, while platforms can enhance features that facilitate real-time interaction and transparency. By bridging theoretical and practical gaps, this research underscores the centrality of trust in LSC success and provides a roadmap for stakeholders to optimize viewer engagement in China's rapidly evolving digital marketplace.

Keywords: Live streaming commerce; morality in the LSC field; expertise; responsiveness; affinity; consumer trust.

INTRODUCTION:

The global growth of internet economies has transformed e-commerce into a dominant retail model, enabling consumers to purchase goods online without physical store visits. However, a novel model, live-streaming commerce (LSC), has emerged in China since 2016, blending live video streaming with real-time product promotion and sales (WEIBOYI, 2022). Unlike traditional e-commerce, LSC leverages interactive features like live demonstrations, instant feedback, and entertainment to engage viewers, attracting both seasoned and new online shoppers (Ganbold, 2024; Chevalier, 2024). While LSC retains standard online payment systems, its reliance on real-time interaction addresses a critical challenge in traditional e-commerce: the physical separation between buyers, sellers, and products. This separation often heightens information asymmetry and perceived transaction risks, making consumer trust a pivotal factor for success (Wongkitrungrueng & Assarut, 2020; Lu & Chen, 2021).

China, the birthplace of LSC, dominates the global market (Ki, et al., 2024). The sector's growth accelerated during the COVID-19 pandemic, as lockdowns shifted consumer behavior toward home-based, entertainment-driven shopping. From a valuation of 420 billion yuan in 2019, China's LSC market surged to nearly 5 trillion yuan (≈$700 billion USD) by 2023, with 765 million active live-stream viewers in 2023 (Ou, 2024; Chevalier, 2024). Two platform types dominate: traditional e-commerce platforms (e.g., Taobao, JD.com) and short-video platforms like Douyin (TikTok's Chinese counterpart) and Kuaishou. This study focuses on Douyin (Or called TikTok), where a trend since 2021 has seen influencers as social media personalities with niche expertise and large follower bases, transition into live-stream sellers (Abidin, 2018; Chen et al., 2023). These "influencer-streamers" monetize their credibility by promoting products directly to audiences, earning commissions while enhancing brand visibility (Rosário et al., 2023). Douyin's live commerce transactions grew 40-fold between 2019 and 2022, underscoring the model's profitability (Chevalier, 2024).

Despite its commercial significance, academic research on Douyin's LSC ecosystem remains limited. Existing studies focus on influencer marketing broadly, such as user motivations (Yang & Ha, 2021), perceptions of endorsed products (Deng et al., 2022), and follower engagement (Barta et al., 2023), advertisements for online retailers (Chaure et al., 2024), while a lack of attention on LSC-specific dynamics. Trust-building as critical in mitigating transaction risks is particularly understudied in the context of influencer-led live streaming. This gap hinders actionable insights for stakeholders: influencers seeking to monetize their reach, brands aiming to leverage partnerships, and platforms like Douyin optimizing their commercial infrastructure.

By examining trust dynamics in Douyin's influencer-led LSC, this study addresses a pressing theoretical and practical need. It explores how influencers-turned-streamers cultivate consumer trust, a factor pivotal to purchase intentions, and provides actionable strategies to enhance platform profitability and stakeholder collaboration. Findings will enrich the limited literature on LSC while offering practical guidance for China's rapidly evolving digital marketplace.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Trust dynamics in influencer-led live streaming commerce

Trust has long been recognized as a cornerstone of e-commerce success, mitigating risks associated with the physical separation of buyers, sellers, and products (Wongkitrungrueng & Assarut, 2020). Traditional online retail struggles with information asymmetry, where customers cannot directly inspect goods or interact with sellers, heightening perceived transaction risks (Lu & Chen, 2021). LSC, pioneered in China, attempts to bridge this gap by integrating real-time interaction, product demonstrations, and entertainment into the shopping experience (Ganbold, 2024). Unlike conventional e-commerce, LSC leverages streamers which are often influencers or sellers, to engage audiences through responsiveness (e.g., answering questions, personalized recommendations) and emotional connection, fostering immediacy and transparency (Chevalier, 2024). Previous studies suggest these dynamics can reduce uncertainty about product quality and fit, directly influencing purchase intentions (Lu & Chen, 2021).

The rapid growth of China's LSC market that from 420 billion yuan in 2019 to 5 trillion yuan (≈$700 billion USD) in 2023, underscores its transformative impact (Ou, 2024). Platforms like Douyin (TikTok's Chinese counterpart) have been instrumental in this growth, particularly through the rise of "influencer-streamers": social media personalities who monetize their credibility by promoting products during live sessions (Chen et al., 2023; Rosário et al., 2023). Influencers' pre-established follower bases and perceived authenticity differentiate this model from brand-led streams, as audiences often view influencers as relatable peers rather than corporate representatives (Abidin, 2018; Barta et al., 2023). This shift aligns with the Stimulus-Organism-Response (S-O-R) framework, where streamer characteristics (stimuli) shape viewer trust (organism), ultimately driving purchasing behavior (response). However, while prior research has examined general influencer marketing, such as follower motivations (Yang & Ha, 2021) or perceptions of endorsed products (Deng et al., 2022), few studies explore how trust is cultivated specifically in the high-velocity, interactive context of LSC.

Existing literature identifies key trust drivers in e-commerce, including seller expertise, responsiveness, and platform security (Wongkitrungrueng & Assarut, 2020). In LSC, however, the real-time, performative nature of streaming introduces unique factors. For instance, streamer affinity, defined as the emotional bond formed through humor, storytelling, or shared interests, may surpass traditional expertise in building trust (Ganbold, 2024). Similarly, streamer morality, such as transparent disclosure of sponsorships or ethical sales tactics, could moderate the trust-purchase intention link, though this remains untested (Rosário et al., 2023). Notably, Douyin's influencer-led model presents a critical yet understudied scenario: influencers transitioning into streamers must balance commercial goals with the authentic persona that initially attracted followers, a tension that may erode trust if poorly managed (Chen et al., 2023).

Despite LSC's commercial significance, academic work remains fragmented. Most studies focus on transactional metrics (e.g., sales growth) or broad platform trends, neglecting the psychological and behavioral mechanisms underpinning trust. This gap limits actionable insights for stakeholders (streamers) seeking to optimize engagement, brands vetting influencer partners, and platforms designing trust-enhancing features. By interrogating how influencer-streamers on Douyin build and sustain trust, this study advances both theoretical frameworks (e.g., S-O-R) and practical strategies, addressing a vital need in the evolving landscape of digital commerce.

2.2 S-O-R model in LSC

The S-O-R (Stimulus-Organism-Response) model, introduced by Woodworth (1929) and refined by Mehrabian and Russell (1974), examines how external stimuli (S) trigger internal cognitive/emotional processes (O) to shape behavioral outcomes (R). Bitner (1992) expanded this by integrating cognitive and emotional responses, while Jacoby (2002) emphasized humans' bounded rationality, arguing decisions are influenced by emotions, social cues, and information constraints. For instance, consumers often rely on advice or past experiences rather than purely rational analysis when purchasing.

The model's adaptability has spurred applications across fields. In consumer behavior, studies explore VR tourism experiences (Kim et al., 2018), mobile dining's impact on perceived value (Shah et al., 2020), and online brand communities (Ul Islam & Rahman, 2017). Recent research applies S-O-R to LSC, where real-time interactions drive consumer actions. Ming et al. (2021) linked social presence and trust to impulsive buying, while Huang et al. (2020) tied cognitive/affective states to purchase intent. Xu et al. (2020) identified streamer traits and interaction quality as key stimuli influencing viewer behavior. Leng (2024) indicated that in-store interaction and psychological intention play significant mediating roles in influencing automobile consumers' impulsive purchase intentions and overall satisfaction, linking the use of short videos to consumer behavior

In the context of LSC, Stimulus refers to environmental cues like product displays, streamer interactions, or real-time engagement (Gao et al., 2018). Streamer charisma and platform features also act as stimuli (Xu et al., 2020). Organism encompasses cognitive/emotional mediators (e.g., trust) linking stimuli to responses (Wu & Li, 2018). Trust, shaped by streamer authenticity, often drives purchase intent in LSC. Response includes behavioral outcomes like purchases, content sharing, or impulsive consumption (Chen et al., 2022). For example, interactive live streams heighten emotional engagement, prompting unplanned buying (Xu et al., 2020; Lu & Chen, 2021).

By bridging psychological processes and environmental triggers, the S-O-R framework remains pivotal in analyzing modern consumer behavior, particularly in dynamic digital environments like LSC. Its integration of emotional, cognitive, and situational factors offers a robust lens for understanding decision-making complexity.

2.3 Purchasing intention

Koufaris (2002) established foundational online consumer behaviors including repurchase, unplanned, and general purchase intentions, providing a framework for studying purchase intention. Defined as an individual's willingness to buy a specific product (Chang & Wildt, 1994), purchase intention is shaped by perceptions of price, quality, and value (Mirabi et al., 2015). Unlike traditional shopping, online purchase intention reflects channel-specific decision-making (Peña-García et al., 2020), influenced by distinct factors such as perceived information risk (Salisbury et al., 2001) and digital engagement behaviors (Zheng et al., 2022). Electronic word-of-mouth (Rafqi Ilhamalimy & Ali, 2021), perceived value, and uncertainty (Guo et al., 2021) further shape intentions in cross-border e-commerce, while platform and brand attitudes directly correlate with purchase decisions in LSC (Yan, 2022). Critically, purchase intention signifies a consumer's primary commitment to engage in LSC; its loss often leads to disengagement, such as exiting live streams (Hou et al., 2019; Wu & Huang, 2023).

Purchase intention is pivotal for predicting actual buying behavior and evaluating marketing efficacy in LSC. It offers insights into how trust, interaction quality, and influencer traits drive consumer decisions which is an area underexplored in Douyin (TikTok) live commerce. Despite existing research on general e-commerce drivers, the unique dynamics of live-streaming platforms such as real-time interaction, influencer authenticity, and platform-specific trust mechanisms, warrant deeper analysis. Understanding these factors can help optimize strategies to sustain consumer engagement and conversion in rapidly evolving digital markets.

2.4 Trust in streamers

Trust is a cognitive shortcut enabling individuals to act on positive expectations of others' reliability without exhaustive analysis (Lewicki & Brinsfield, 2011). In transactions, it reduces uncertainty by fostering perceptions of mutual dependability (Gambetta, 2000). For e-commerce, trust encompasses consumers' beliefs about sellers' integrity, product quality, and platform security (McKnight et al., 2002; Kim et al., 2008), directly influencing purchase decisions. A lack of trust diminishes online engagement, making risk mitigation and trust-building critical for sustaining purchase intentions (Meskaran et al., 2013).

In LSC, trust mediates consumer behavior through dynamic interactions. Streamers bridge information gaps by demonstrating products in real time, making intangible items tangible (Xu et al., 2022). Studies confirm trust's indirect effect on purchase intentions: Chinese consumers' trust in LSC enhances engagement (Ma et al., 2022), while trust in both streamers and products drives repeat purchases (Wu & Huang, 2023). Emotional trust further links contextual factors like product appeal or atmosphere to purchase intent (Zhou & Tong, 2022). These findings, grounded in frameworks like information asymmetry and parasocial relationship theories, position trust as a central mediator in the S-O-R model (Xu et al., 2022; Ma et al., 2022).

However, existing research gaps persist. While trust's role is well-established, its conceptualization often lacks granularity. Some studies treat "trust" monolithically (e.g., Ma et al., 2022; Ming et al., 2021), whereas others distinguish dimensions like trust in streamers versus trust in products. For instance, Wongkitrungrueng and Assarut (2020) show product confidence cascades into seller trust, while Zhang et al. (2022a) find trust in streamers transfers to product recommendations, boosting platform loyalty. This underscores trust's transferability across LSC contexts. Additionally, antecedents of trust such as interaction quality or influencer authenticity, vary across studies (Wu & Huang, 2023; Chen & Zhou, 2022). Alalwan et al. (2017) note trust drivers evolve with user-platform interactions, raising questions about whether prior findings apply to short-video platforms like Douyin, where real-time engagement and algorithmic curation redefine trust dynamics.

In summary, while trust's mediating role in LSC is clear, its multidimensionality and contextual fluidity demand deeper inquiry. Current literature addressing how platform-specific features reshape trust-building mechanisms remains limited.

Based on the previously mentioned literature review, this study proposes the following hypothesis to validate the influence of different trust priors on trust, purchase intention, and the role trust plays:

H1: Consumer's trust in streamers in LSC positively affects purchase intention.

2.5 Streamers' characteristics in LSC

Drawing on the S-O-R framework, this study investigates how streamers' characteristics including expertise, responsiveness, affinity, and morality, act as stimuli shaping consumer trust and purchase intentions in LSC on platforms like Douyin (TikTok). Below, we synthesize key literature and hypotheses guiding this exploration.

2.5.1 Expertise

Expertise in LSC reflects a streamer's ability to deliver specialized product knowledge and guide purchasing decisions. While traditional sales roles emphasize professionalization, live streaming demands broader competence as influencers often promote diverse products (He et al., 2022; Chen et al., 2023). Platforms like TikTok empower streamers to share detailed usage insights and engage viewers via real-time interactions (e.g., the "bullet screen" feature), directly showcasing their expertise (Ko & Chen, 2020).

Empirical studies highlight expertise's role in enhancing trust, immersive experiences, and purchase intentions (Huang et al., 2020; Liao et al., 2022). For instance, streamers who address consumer concerns promptly and offer tailored recommendations strengthen perceived credibility (Guo et al., 2022; Ma et al., 2022). However, gaps remain in understanding how platform-specific dynamics (e.g., Douyin's influencer-led model) shape this relationship. This study addresses these gaps with the following hypotheses:

H2: Streamer expertise positively affects viewer trust in Douyin LSC.

H2a: Trust mediates the relationship between expertise and purchase intention.

2.5.2 Responsiveness

Responsiveness refers to a streamer's capacity to engage viewers through timely, relevant interactions. Unlike platform-driven synchronicity (real-time messaging features), responsiveness reflects the streamer's active role in addressing questions, resolving technical issues, and fostering intimacy (Kang et al., 2021; Zhang et al., 2022a). Effective responsiveness balances speed and relevance: over-engagement risks viewer fatigue, while under-engagement weakens interactivity (Guan et al., 2021; Kang et al., 2021).

In Douyin's fast-paced environment, streamers must navigate unpredictable scenarios (e.g., offensive comments, payment glitches) to maintain trust. Studies link responsiveness to emotional engagement and purchase intent (Li et al., 2022; Zhang et al., 2020), yet few isolate its unique impact on trust. We propose:

H3: Streamer responsiveness positively affects viewer trust in Douyin LSC.

H3a: Trust mediates the relationship between responsiveness and purchase intention.

2.5.3 Affinity

Affinity, rooted in perceived similarity and warmth, enables streamers to build emotional bonds with viewers. Tactics like addressing audiences as "friends" or sharing personal anecdotes foster communal belonging (Zhang et al., 2022b). For example, top Chinese streamers Austin Li and Weiya cultivate intimacy by discussing health tips and product benefits in relatable terms.

While affinity's role in LSC is underexplored, qualitative insights suggest that approachable, non-aggressive communication styles enhance trust (Guo et al., 2022; Zhang et al., 2022b). This study extends this concept to Douyin's influencer-led model, hypothesizing:

H4: Streamer affinity positively affects viewer trust in Douyin LSC.

H4a: Trust mediates the relationship between affinity and purchase intention.

2.5.4 Morality

Morality encompasses a streamer's adherence to ethical norms, such as honesty and social responsibility, which shape their public image. Unethical behavior (e.g., promoting low-quality products) erodes trust and triggers platform penalties (Zhou & Whitla, 2013). Conversely, moral conduct, such as transparently disclosing sponsorships, strengthens credibility and purchase intent (Chen et al., 2024; Wang & Wang, 2021).

Emerging research posits morality as a moderator: ethical streamers amplify trust's impact on purchases, while scandals negate it (Grgurić Čop et al., 2023). In China's tightly regulated LSC landscape, this relationship is critical yet understudied. We propose:

H5: Streamer morality positively moderates the trust-purchase intention relationship.

2.6 Research framework
Building on the aforementioned hypotheses and grounded in the S-O-R model, we propose a research framework (illustrated in Figure 1) where the three streamer characteristics function as independent variables, trust in the streamer acts as the mediator, and purchase intention serves as the dependent variable. Furthermore, we introduce live streamer morality as a moderating variable that influences the relationship between trust and purchase intention.
[Insert Figure 1 Here]

METHODOLOGY
The methodological approach of this study is grounded in the most prevalent and widely utilized practices within prior research in the field of LSC. Specifically, this involves quantifying the attitudes and perceptions of live streaming consumers through quantitative research methods. Data is collected via online surveys and subsequently analyzed using SPSS to validate the hypotheses.

3.1 Research procedures
This study adopted an online questionnaire administered in English to align with prior similar studies. However, given that the research focuses on the Chinese market and the live streaming shopping behaviors of Chinese consumers, to address this linguistic challenge and ensure the accuracy and fidelity of the translation, we utilized the back-translation method as outlined by Brislin (1970).

The study engaged two anonymous translators, both proficient in Chinese and English and holding master's degrees from universities in the UK. The first translator translated the original English questionnaire into simplified Chinese, while the second translator independently back-translated the Chinese version into English. By carefully comparing the back-translated version with the original, the study identified and resolved inconsistencies, adjusting the tone and style of the questionnaire as needed. This meticulous process was implemented to ensure that the questionnaire accurately reflected the context of LSC in China, thereby enhancing the validity and reliability of the research.

3.2 Variable measurement and description
The measurement items used in this study encompass Perceived Streamers' Characteristics by Viewers, Trust in Streamers, Purchase Intention, Extraversion, and Neuroticism (see Table 1). The questionnaire utilized a five-point Likert scale, where scores ranged from 1 to 5, corresponding to "1: Strongly Disagree", "2: Disagree", "3: Neutral", "4: Agree", and "5: Strongly Agree" (Likert, 1932). As detailed in Table 1, the definitions and measures for each variable were drawn from prior studies and subsequently adapted to align with the specific context of this research.

Table 1. Variable measurement

Constructs	Items	Measurement	Reference
Expertise (ET)	ET1	Streamers are highly experienced in live streaming and sales.	(Guo et al., 2022)
	ET2	Streamers are highly knowledgeable about products they promote	
	ET3	Streamers provide extensive information about products.	
	ET4	Streamers have product experience personally.	(Rungruangjit, 2022)
Responsiveness (RS)	RS1	Streamers tell viewers information of products and service accurately.	(Zhang et al., 2020), (Zhang et al., 2022b)
	RS2	Streamers respond to viewers 'questions quickly.	(Hou et al., 2019)
	RS3	Streamers have high response rate to questions posed by bullet screens	(Kang et al., 2021)
	RS4	Streamers have excellent on-the-spot resilience.	(Zhang et al., 2022b)
Affinity (AF)	AF1	Streamers are very friendly, Gentle, and non-aggressive	(Zhang et al., 2022b) (Nes et al., 2014)
	AF2	Streamers have high sense of humor.	(Nes et al., 2014)
	AF3	Streamers are easy-going, very approachable and there's short distance between viewers.	(Zhang et al., 2022b) (Nes et al., 2014)
	AF4	Streamers provide high sense of attachment to viewers	(Oberecker & Diamantopoulos, 2011)
Trust in streamers (TS)	TS1	Viewers are convinced by the information provided by streamers	(Zhang et al., 2022a) (Wongkitrungrueng & Assarut, 2020)
	TS2	Viewers don't think the streamers take advantage of them	
	TS3	Viewers believe that streamers are trustworthy.	

	TS4	Viewers are confident that the streamer is well-intentioned and will consider the buyer's basic interests.	(Wu & Huang, 2023)
Purchase intention (PI)	PI1	The product the streamer recommends is worth buying.	(Park & Lin, 2020); (Liao et al., 2022) (Rungruangjit, 2022)
	PI2	Viewers are willing to try the product the streamer recommends.	(Park & Lin, 2020); (Liao et al., 2022) (Zhang et al., 2020) (Rungruangjit, 2022)
	PI3	Viewers would like to recommend friends and family to purchase products from streamers.	(Park & Lin, 2020); (Liao et al., 2022) (Zhang et al., 2020) (Meng et al., 2021)
	PI4	Viewers will buy products that are recommended by streamers in the future.	(Rungruangjit, 2022) (Meng et al., 2021)
Live streamer morality (LSM)	LSM1	Live streamers are sincere to viewers	(Davies et al., 2004) (Wang & Wang, 2021) (Chen et al., 2024) (Zhou & Whitla, 2013)
	LSM2	Live streamers are socially responsible	
	LSM3	Live streamers are honest to viewers.	
	LSM4	Live streamers do not promote harmful products.	(Grgurić Čop et al., 2023)

This study measured three streamer characteristics as independent variables, grounded in established literature:

1) Expertise (ET) integrates definitions from Guo et al. (2022) and Rungruangjit (2022), emphasizing streamers' ability to combine extensive sales experience, product knowledge, and firsthand usage to deliver authoritative guidance for informed purchasing decisions;
2) Responsiveness (RS) reflects streamers' capacity to communicate product details clearly, address viewer inquiries promptly, and maintain seamless interactions to ensure satisfaction (Hou et al., 2019; Kang et al., 2021; Zhang et al., 2022);
3) Affinity (AF), less explored in LSC, synthesizes Zhang et al.'s (2022b) qualitative insights with scales from Nes et al. (2014) and Oberecker and Diamantopoulos (2011). It captures streamers' approachability, humor, and ability to foster viewer rapport, cultivating a welcoming and dependable atmosphere.

Trust in streamers (TS), a mediating variable in the S-O-R framework, denotes viewers' confidence in streamers' sincerity, belief that their interests are prioritized, and assurance that they are not exploited (Wongkitrungrueng & Assarut, 2020; Wu & Huang, 2023; Zhang et al., 2022a). This construct bridges consumer-seller relationships in LSC.

Purchase intention (PI), the dependent variable, represents consumers' willingness to buy, try, and recommend streamer-endorsed products, as well as their intent to repurchase in the future (Park & Lin, 2020; Liao et al., 2022; Rungruangjit, 2022; Meng et al., 2021).

Live Streamer Morality (LSM) moderates the trust-purchase intention relationship. Synthesizing interdisciplinary literature, LSM encompasses honesty, integrity, and consumer-centric sincerity (Wang, 2021; Chen et al., 2024). Ethical lapses, such as promoting harmful products for profit, undermine consumer trust and loyalty (Grgurić Čop et al., 2023). Prior studies highlight that perceived ethical responsibility significantly shapes brand reputation (Davies et al., 2004), and unethical influencer practices damage consumer perceptions (Zhou & Whitla, 2013).

3.3 Questionnaire design and recruitment

The questionnaire was distributed via the University of Auckland's Qualtrics platform. To reach Chinese adults with live shopping experience, the study's link and QR code were shared on popular Chinese social media platforms like WeChat and Weibo.

The survey, designed with single-choice questions, took 5-10 minutes to complete. It began with the University of Auckland's ethics approval (Reference Number: UAHPEC27019), followed by an explanation of the study's purpose, participant rights (e.g., the option to withdraw), and privacy assurances. The questionnaire was divided into three sections. The first collected demographic information, while the second assessed participants' familiarity with the mixed streaming model (Chen et al., 2023). Those unfamiliar with the model could exit at this stage. This section also included questions on shopping and viewing frequency. The final section focused on live streamer characteristics, trust, and ethics, with all questions derived from prior literature.

3.4 Survey design and data collection

3.4.1 Pilot test

A pilot study assessed the clarity and accuracy of the questionnaire, particularly the Chinese translation, to ensure respondents understood the concepts of LSC. Thirty valid responses were collected via the University of Auckland's Qualtrics platform. While the measurement items proved reliable and participants understood the variables, some respondents provided incomplete or non-responsive answers, likely due to the voluntary nature of the pilot. The pilot data were excluded from the final sample, and the revised version incorporated more detailed descriptive items from prior literature to enhance clarity.

3.4.2 Sample collection results

The revised questionnaire comprised 31 questions, with 24 main items on a 5-point Likert scale. Data collection concluded in early June 2024, yielding 214 valid responses from an initial 240 submissions after excluding incomplete entries. The sample size met the minimum requirement for Partial Least Squares (PLS) analysis, as per the "10-fold" method (Hair et al., 2013), which estimates sample sizes for PLS-based structural equation modeling (SEM). With 24 observed indicators, the sample of 214 was deemed sufficient for this niche study, ensuring statistical power and reliability.

3.4.3 Sample Characteristics

Table 2 summarizes the sample demographics. Females slightly outnumbered males (115 vs. 98), representing 53.7% of respondents, consistent with the 2022 China Live Streaming E-Commerce Opportunity Insight Report, which found that 53.8% of live streaming orders were placed by females (WEIBOYI, 2022). This alignment enhances the study's credibility and reflects broader market trends.

The 26-35 age group dominated the sample, comprising 50.93% (109 respondents), indicating higher engagement with live streaming commerce among younger consumers. In contrast, only 4.21% (9 respondents) were over 45, suggesting older consumers may be less receptive to this shopping method.

Nearly all respondents (99.07%) were citizens of the People's Republic of China, including Hong Kong and Macau residents, underscoring the study's focus on the Chinese LSC market.

Education levels were relatively high, with 65.42% holding undergraduate degrees and 17.76% possessing postgraduate qualifications. Over 83% of the sample had completed higher education, likely contributing to their awareness of live shopping trends and pursuit of quality lifestyles.

Most respondents regularly engaged with live shopping streams, with 50.93% watching 5-10 times monthly. This sustained interest highlights their familiarity with the live streaming model, making them an appropriate target audience for this study.

Douyin (TikTok) Live and Taobao Live were the preferred platforms, chosen by 50.47% (108 respondents) and 44.86% (96 respondents), respectively. These findings align with the platforms' dominance in China's live streaming sector, reinforcing the study's relevance to the Douyin (TikTok) live streaming market.
Therefore, the sample's demographic and behavioral characteristics reflect key trends in China's LSC market, ensuring the study's findings are both credible and representative of the target population.

Table 2. Sample demographics

Category	**Options**	**Frequency**	**Percentage (%)**
Gender	Male	98	45.79
	Female	115	53.74
	Others	1	0.47
Age	18-25	32	14.95
	26-35	109	50.93
	36-45	64	29.91
	Over 45	9	4.21
Nationality	People's Republic of China (including HK and Macau)	212	99.07
	Other countries and regions	2	0.93
Education	Middle school or less	6	2.80
	High school	30	14.02
	College/University UG	140	65.42
	Higher than UG	38	17.76
Live Shopping Frequency (monthly)	Only on special occasions	9	4.21
	Less than 5 times per month	75	35.05
	5-10 times per month	109	50.93

Table 2. Sample demographics

Category	**Options**	**Frequency**	**Percentage (%)**
	More than 10 times per month	21	9.81
Preferred platform	DOUYIN (TikTok) Live	108	50.47
	Taobao Live	96	44.86
	Other similar platforms	10	4.67
Total		214	100

4 DATA ANALYSIS AND RESULT

The data in this study were analyzed using SPSS 26.0 and SmartPLS 4.0. SPSS 26.0 was utilized to conduct frequency analysis of the demographic data from the questionnaire and to perform reliability and validity analyses on the scale items. SmartPLS 4.0 was employed to examine the relationships among variables, including discriminant validity, model fit, path analysis, mediation effect analysis, and moderation effect analysis. SmartPLS is capable of analyzing both measurement and structural models and has been widely used in previous relevant studies on LSC (Zhang et al., 2022a; Wongkitrungrueng & Assarut, 2020; Guo et al., 2022). It is particularly well-suited for studies with smaller sample sizes. With a total sample size of 214, the data met the eligibility criteria for analysis.

4.1 Measurement model

4.1.1 Reliability and validity analysis

The study conducted reliability and validity analyses to assess the primary metrics of the measured variables. As shown in Table 3, the validity test of the scale revealed that the Average Variance Extracted (AVE) values for all factors ranged from 0.595 to 0.732, with each dimension exceeding the threshold of 0.5. Additionally, the Composite Reliability (CR) values ranged from 0.778 to 0.898, all surpassing the 0.6 benchmark. These results confirm strong convergent validity and composite reliability across all dimensions. Furthermore, the factor loadings of the measured variables were all above the 0.5 threshold, and the Cronbach's Alpha values for reliability ranged from 0.774 to 0.879, exceeding the 0.7 threshold. These findings demonstrate high internal consistency, indicating the robustness of the measurement model.

Table 3. Reliability and validity analysis

	Loading	Cronbach Alpha	CR	AVE
AF1	0.820	0.836	0.867	0.667
AF2	0.805			
AF3	0.767			
AF4	0.870			
ET1	0.750	0.774	0.778	0.595
ET2	0.796			
ET3	0.792			
ET4	0.746			
LSM1	0.827	0.879	0.890	0.732
LSM2	0.870			
LSM3	0.858			
LSM4	0.867			
PI1	0.803	0.847	0.850	0.686
PI2	0.823			
PI3	0.817			
PI4	0.867			
RS1	0.777	0.830	0.898	0.650
RS2	0.835			
RS3	0.852			
RS4	0.756			
TS1	0.833	0.841	0.842	0.676
TS2	0.835			
TS3	0.802			
TS4	0.820			

The study employed standard validation methods in assessing convergent validity, including the Fornell-Larcker criterion (1981). According to the results presented in Table 4, the discriminant validity test demonstrated that the square roots of the AVE values for each dimension were substantially more significant than the corresponding inter-construct correlations. This comparison between the standardized correlation coefficients of the dimensions and the square roots of the AVE values provides evidence for adequate discriminant validity. Consequently, the variables display good discriminant validity.

Table 4. Discriminant Validity (Fornell-Larcker criterion)

	AF	ET	LSM	PI	RS	TS
AF	0.817					
ET	0.136	0.771				
LSM	0.183	0.279	0.856			
PI	0.298	0.328	0.436	0.828		
RS	0.153	0.203	0.275	0.300	0.806	
TS	0.344	0.261	0.142	0.478	0.272	0.822

4.2 Structural model and hypothesis testings

4.2.1 Model fit analysis

In the model fit analysis presented in Table 5, the Standardized Root Mean Square Residual (SRMR) value for the saturated model was 0.063, while the estimated model had an SRMR value of 0.065. The Normed Fit Index (NFI) for the saturated model was 0.795, compared to 0.791 for the estimated model. According to the criteria established by Hu and Bentler (1999), an SRMR value of less than 0.1 is considered acceptable. Additionally, the values for d_ULS and d_G should ideally be less than 0.95, and an NFI greater than 0.70 is also recommended.

Although the NFI values in this analysis are not particularly high, they remain within an acceptable range, especially considering the limited number of variables included in this study.

Table 5. Model fit

	Saturated Model	Estimated Model
SRMR	0.063	0.065
d_ULS	1.198	1.256
d_G	0.400	0.408
Chi-square	499.726	508.327
NFI	0.795	0.791

4.2.2 Path analysis

In the path analysis (shown in Table 6), the coefficient for Affinity on trust in streamers was 0.290 ($t = 4.720$, $p < 0.001$), indicating a significant positive effect; this result supports Hypothesis 4 (H4). The Expertise coefficient was 0.183 ($t = 2.667$, $p = 0.008$), demonstrating a positive influence on trust and supporting Hypothesis 2 (H2). Additionally, Responsiveness had a coefficient of 0.191 ($t = 3.266$, $p = 0.001$), confirming its significant positive effect on trust and supporting Hypothesis 3 (H3). Together, these findings show that while all three characteristics impact trust in streamers, they do so to varying degrees. The model achieved a squared multiple correlation (R^2) of 0.200 for trust, indicating an acceptable level of explained variance, likely due to the limited number of independent variables assessed.

In another analysis, trust in streamers significantly affected purchase intention, with a path coefficient of 0.388 ($t = 6.165$, $p < 0.001$), strongly supporting Hypothesis 1 (H1). The model explained 41.8% of the variance in purchase intention ($R^2 = 0.418$), reflecting good explanatory power in this relationship.

Table 6. Structural path analysis

	β	SE	T	p	2.50%	97.50%	Conclusion
AF -> TS	0.290	0.062	4.720	0.000	0.165	0.407	Supported
ET -> TS	0.183	0.069	2.667	0.008	0.04	0.307	Supported
RS -> TS	0.191	0.058	3.266	0.001	0.067	0.296	Supported
TS -> PI	0.388	0.063	6.165	0.000	0.260	0.507	Supported

4.2.3 Mediation Effect Test

Table 7 presents the path coefficients that illustrate the influence of various factors on target and purchase intention. The path coefficient for affinity to trust in streamers to purchase intention (AF -> TS -> PI) is the highest at 0.113, indicating that affinity significantly affects purchase intention through trust in streamers. The coefficients for responsiveness to trust in streamers to purchase intention (RS -> TS -> PI) and expertise to trust in streamers to purchase intention (ET -> TS -> PI) are 0.074 and 0.071, respectively. While these values are slightly lower than AF -> TS -> PI, they still reflect a meaningful level of significance.

The standard deviation measures the variability of these path coefficients. The standard deviation for AF -> TS -> PI is 0.033, indicating stability in this coefficient. Similarly, the standard deviations for RS -> TS -> PI and ET -> TS -> PI are 0.027 and 0.031, respectively, further demonstrating stability.

To assess the significance of the path coefficients, we examine the T-statistic and p-value. At a significance level of 0.05, the T-statistic for AF -> TS -> PI is 3.461 with a p-value of 0.001, confirming its statistical significance. The T-statistics for RS -> TS -> PI and ET -> TS -> PI are 2.722 and 2.320, respectively, with p-values of 0.007 and 0.020, also indicating significance.

The 2.50% and 97.50% columns represent the confidence intervals for the path coefficients. None of these intervals include zero, further validating the significance of the coefficients. Consequently, the results support H2a, H3a, and H4a, suggesting that trust in streamers mediates the relationship between live streamer characteristics (expertise, responsiveness, and affinity) and purchase intention.

Table 7. Mediation effect test

	β	SE	T	p	2.50%	97.50%	Conclusion
AF -> TS -> PI	0.113	0.033	3.461	0.001	0.058	0.185	Supported
RS -> TS -> PI	0.074	0.027	2.722	0.007	0.030	0.137	Supported
ET -> TS -> PI	0.071	0.031	2.320	0.020	0.019	0.138	Supported

4.2.4 Moderation effect test

Confirmatory factor analysis results are presented in Table 8, and the moderation effect analysis is shown in Table 8. the study utilized Smart-PLS 4.0 and employed the Bootstrap method with 5,000 iterations to obtain confidence intervals for both direct and interaction effects. The path coefficient for the relationship between trust in streamers (TS) and purchase intention (PI) was 0.388 ($t = 6.165$, $p < 0.001$), indicating a significant positive effect. Similarly, the path coefficient for live streamer morality (LSM) on purchase intention was 0.306 ($t = 4.411$, $p < 0.001$), also demonstrating a significant positive effect.

For the interaction term with variable D as the moderator, the effect of "LSM x TS on PI" had a path coefficient of 0.252 ($t = 3.726$, $p < 0.001$), with a confidence interval of [0.110, 0.376], which does not include zero. This finding suggests that live streamer morality positively moderates the relationship between trust in streamers and purchase intention, thus supporting Hypothesis 5 (H5).

This implies that when viewers perceive live streamers as ethical and moral, they are more likely to intend to make purchases during the live stream, as their trust in the streamers increases. Conversely, if viewers do not perceive the streamers as ethical or fail to observe ethical behavior or statements, their purchase intention may be adversely affected.

Table 8. Confirmatory factor analysis results

	β	SE	T	p	2.50%	97.50%	Conclusion
TS -> PI	0.388	0.063	6.165	0.000	0.260	0.507	/
LSM -> PI	0.306	0.069	4.411	0.000	0.162	0.436	/
LSM x TS -> PI	0.252	0.068	3.726	0.000	0.110	0.376	Supported

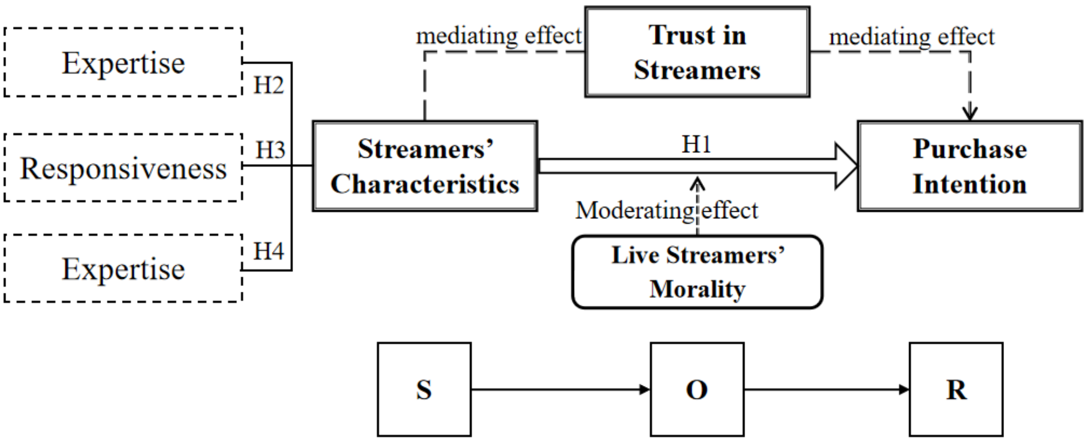

Figure 1. Conceptual framework

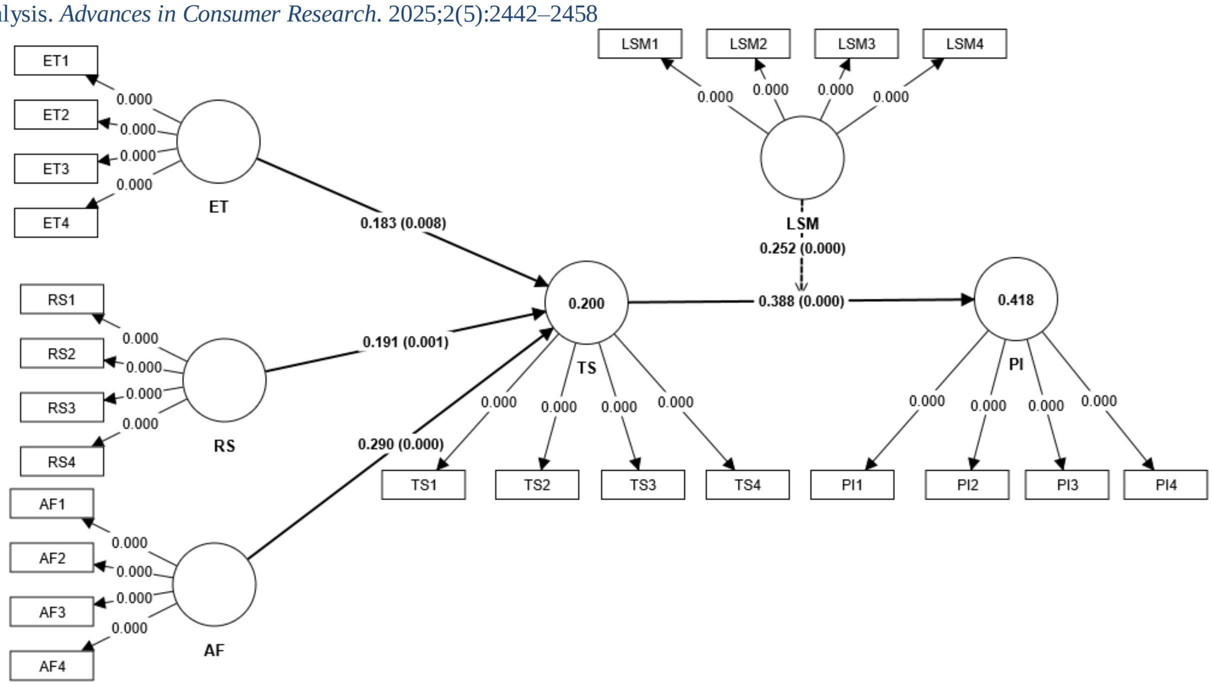

Figure 1. Results of structural model

Note: ∗p < .05; ∗∗p < .01; ∗∗∗p < .001. note: p < 0.05: "statistically significant."; p < 0.01: "very statistically significant"; p < 0.001: "highly statistically significant"; NS: "non-significant"

DISCUSSION

This study examines how trust in Douyin (TikTok) live streamers enhances viewers' purchase intentions, focusing on three key streamer traits including expertise, responsiveness, and affinity, and the moderating role of streamer morality. A new model, grounded in the S-O-R framework, demonstrates how these traits foster trust and drive purchasing decisions. The results validate the model's applicability to real-time LSC, highlighting the interplay between streamer attributes, trust, and consumer behavior. All hypotheses are supported, confirming the model's relevance to LSC research. The key results include:

1) Effectiveness of the S-O-R model

The S-O-R model effectively explains consumer behavior in LSC. Streamer characteristics serve as external stimuli that build trust, which in turn influences purchase intentions. This aligns with prior research showing the S-O-R model's utility in studying customer engagement, hedonic consumption, and impulse buying (Kang et al., 2021; Xu et al., 2020). While earlier studies focused on different goals, they similarly highlight the framework's ability to capture real-time interactions and transient consumer behaviors, making it highly applicable to LSC. This study further confirms the S-O-R model's relevance to short video platforms like Douyin.

2) Trust in streamers and purchase intention

Trust in streamers significantly and positively influences viewers' purchase intentions. Streamers earn trust through their words and actions, which reduces uncertainty about product quality and alleviates consumer concerns. This finding aligns with prior research (Lu & Chen, 2021; Wu & Huang, 2023), which shows that trust mitigates product-related distress and boosts purchase intentions. Additionally, trust fosters viewer engagement, encourages repeat purchases, and sustains platform usage (Wongkitrungrueng & Assarut, 2020; Zhang et al., 2022a). This study extends existing research by confirming these dynamics within the Douyin context, emphasizing the critical role of trust in LSC.

3) Streamer characteristics and trust

Streamer expertise, responsiveness, and affinity significantly enhance viewers' trust. Expertise, which demonstrated through product knowledge, establishes credibility, while responsiveness, reflected in timely interactions, shows engagement and commitment. Affinity, characterized by a friendly and relatable demeanor, fosters intimacy with viewers. Among these traits, affinity has the strongest positive effect on trust, corroborating findings from Zhang et al. (2022b). This study quantifies the impact of these characteristics, deepening understanding of how streamer traits influence trust dynamics in LSC.

4) Mediation and Moderation Effects

Trust mediates the relationship between streamer characteristics and purchase intentions. When viewers perceive streamers as knowledgeable, responsive, and relatable, their trust increases, driving purchase intentions. Affinity, in particular, has a more pronounced effect on purchase intentions than expertise or responsiveness, likely due to the unique context of short video platforms like Douyin. These platforms allow viewers to easily access streamers' content, fostering a positive and approachable image.

Streamer morality also plays a significant moderating role, strengthening the relationship between trust and purchase intentions. Higher ethical standards, such as honesty and social responsibility, enhance the trust-purchase intention link. This underscores the importance of moral behavior in LSC; trust alone is insufficient. Streamers who demonstrate high morality are more effective at driving purchase intentions, as viewers perceive their recommendations as more credible and reliable.

CONCLUSION

Using the S-O-R theoretical framework, this study examines how streamer characteristics and moral behaviors influence trust and viewers' purchase intentions on Douyin (TikTok) live-streaming platform. The findings reveal that viewers' perceptions of streamer traits act as external stimuli during live-streaming interactions, fostering an internal state of trust that directly impacts purchase intentions. Consequently, the behaviors and comments of streamers are pivotal in encouraging viewer participation in the buying process. The development of a streamer's character and the viewers' resulting decisions shape the extent of this influence.

Trust emerges as a crucial factor driving purchase intentions. Establishing a trusting relationship between streamers and viewers alleviates concerns regarding product quality and information asymmetry. The study shows that trust is a reaction to external stimuli rather than a random occurrence, accurately reflecting consumer purchasing psychology.

All three streamer characteristics positively affect trust. Expertise, a frequently studied aspect in prior research, allows viewers to evaluate a streamer's business acumen based on their responses and understanding of product features. An amateurish appearance can significantly diminish a streamer's credibility. Responsiveness reflects professional competence, such as effectively addressing viewer questions and managing unexpected issues, showcasing the streamer's engagement level. Meanwhile, affinity enhances a streamer's positive image and significantly impacts trust and purchase intention.

Moreover, high moral standards among streamers strengthen the trust-purchase intention relationship, emphasizing the importance for brands, platforms, and viewers. Conversely, unethical behavior can erode trust and hinder viewer engagement.

6.1 Theoretical contributions

This study aims to validate and expand the concept of streamer affinity, which has not been well-defined in previous research. It seeks to establish a positive relationship between streamer affinity and viewers' trust, demonstrating how affinity indirectly influences purchase intentions on Douyin (TikTok) Live. By focusing on affinity's critical role in enhancing trust and its subsequent impact on purchase behavior, the study enriches the LSC knowledge framework, contributing valuable insights into how streamers can effectively engage their audiences.

Additionally, this study utilizes the S-O-R model to examine the role of streamer morality in moderating the relationship between trust and purchase intention. This addresses a gap in existing literature that has not thoroughly explored how morality impacts the trust-purchase intention dynamics in LSC. While prior research, including Chen and Zhou (2022) and Chen et al. (2024), highlights the significance of moral character in fostering cognitive and affective trust, they have not investigated morality as a moderating factor. This study extends previous findings by demonstrating that streamers' moral behavior can strengthen the connection between viewer trust and purchase intention, providing a nuanced perspective on morality's role in shaping consumer behavior.

The research focuses on the influencer-led LSC model prevalent on Douyin (TikTok), analyzing how viewers' trust and purchase intentions are influenced by diverse products promoted by influencers in a live-streaming environment. This study uniquely explores how streamer expertise and responsiveness affect trust and purchase intention, clarifying whether these characteristics stem from the streamer or the platform itself.

In summary, this study investigates the influence of three streamer characteristics on trust and their indirect effects on purchase intentions in the influencer-led LSC context on Douyin (TikTok). Data will be gathered through an online questionnaire, guided by the S-O-R model framework, aligning with existing literature. This research aims to deepen the understanding of these dynamics within the thriving landscape of live streaming commerce.

6.2 Practical implications

The research model and findings offer valuable insights for practitioners aiming to boost profits through improved live performance and consumer purchase intention.

First, influencer management companies should focus not only on nurturing potential influencers but also on maximizing the impact of those who have already established a presence through brand collaborations. This typically involves promoting products during live streams, which requires fostering a strong affinity between streamers and their audience. By creating an environment where viewers feel a personal connection, akin to friends or neighbors, streamers can enhance viewer intimacy. Short-form video platforms can facilitate this by enabling influencers to engage in live sessions that encourage interaction, both in the live room and through social content. Streamers should also target viewers who frequently interact with their content, using engaging language. This study emphasizes the importance of expertise and responsiveness; for instance, streamers should clearly articulate the features and benefits of several products while promptly addressing viewer questions, attributes that signify strong performance and require substantial training.

Second, for influencers, selling products through live streaming necessitates persuading viewers to buy. Companies need to support streamers in generating momentum while adhering to their guidelines. Streamers must balance developing their sales skills with maintaining a positive public image, actively communicating with their companies to avoid promoting problematic products that could damage trust.

Third, the influencer-led live-streaming model allows brands with limited budgets to achieve high visibility by collaborating with multiple influencers. Brands should prioritize the influencer's image, business capabilities, and target audience over the product's fit with the influencer's expertise.

Finally, short video platforms like Douyin (TikTok) and Kuaishou must effectively utilize their extensive user bases. Although they may face distribution and supply chain challenges compared to traditional e-commerce platforms, influencers can leverage their reach to enhance competitiveness. Platforms should carefully select traffic investment targets, weighing the benefits of supporting top streamers against nurturing emerging ones, while considering both selling abilities and moral qualities. This study provides limited recommendations for platforms, emphasizing the importance of balancing risks and benefits.

6.3 Limitations and future research

This study collected 214 valid questionnaires, resulting in a small sample size that may limit the generalizability of the findings. Additionally, variations in economic development and purchasing power across different regions in China were not considered, making it challenging to assess whether the results apply to specific areas.

While the focus is on consumer behavior within the influencer-led live streaming model on Douyin (TikTok), nearly 44.8% of respondents preferred shopping via traditional Taobao live streaming. The significant differences between short video platforms and traditional e-commerce complicate the understanding of personal factors influencing viewer choices. Moreover, as the live streaming commerce (LSC) industry rapidly evolves, platform policies and market dynamics are subject to annual shifts. For instance, during the first phase of the "618" shopping festival in 2024, sales of live-streamed goods fell by nearly 50%, reflecting consumer sophistication and declining trust in top streamers, potentially due to information overload or negative prior experiences (Sina Finance, 2024).

Additionally, significant changes, such as the cancellation of the pre-sale system by major platforms, have adversely affected sales and influencer performance (Jiemian, 2024). These trends suggest that the influence of top streamers may diminish over time, prompting platforms to focus more on mid-level streamers for sales growth. Consequently, while the study's findings offer short-term insights, they cannot predict long-term consumer attitudes or shifts in platform policies.

Future research could focus on validating the concept of streamer affinity with larger, more diverse samples. Additionally, exploring different types of trust could enhance understanding of dynamic consumer trust relationships. Researchers may also categorize specific LSC platforms more rigorously and consider differences between short video and traditional e-commerce. In addition, scholars can adopt a critical lens on the development of live streaming in China to enrich global research on streamer characteristics.

Finally, future studies may distinguish between Douyin and TikTok. Although they share similar frameworks, findings from Douyin may not fully apply to TikTok due to geographic differences. Comparing user behavior across regions, such as between Douyin in China and TikTok in the United States, might yield valuable insights. As LSC integrates into daily life, it is poised for robust growth founded on strong ethical principles.

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