International Review of Management and Marketing

ISSN: 2146-4405

available at http: www.econjournals.com

International Review of Management and Marketing, 2026, 16(3), 256-266.

Integrating Social Interaction and Technology Readiness to Explain Consumer Adoption of Live-Streaming Shopping

Yinbo Zeng*, Jihad Mohammad

UCSI University, Kuala Lumpur, Malaysia. *Email: zengyb0127@qq.com

Received: 21 September 2025 **Accepted:** 03 February 2026 **DOI:** https://doi.org/10.32479/irmm.22416

ABSTRACT

Live streaming shopping has rapidly emerged as a mainstream form of online shopping, but the mechanisms driving consumer purchase intentions and actual purchasing behavior remain insufficiently understood. This study constructs and tests a comprehensive model based on the Technology Acceptance Model (TAM) and Technology Readiness (TR) theories. This model integrates live streaming interactivity, anchor credibility, perceived complexity, trust, intention to use live streaming shopping, and technology readiness as a moderating variable. Using data from 284 Chinese consumers and SmartPLS 4.1 software, the results show that interactivity and anchor credibility significantly enhance trust and purchase intention, while perceived complexity negatively impacts both trust and intention. Trust and purchase intention effectively predict actual purchasing behavior, highlighting their core roles in live streaming shopping. Importantly, technology readiness not only directly affects actual purchasing behavior but also strengthens the link between purchase intention and actual purchasing behavior, indicating that consumers with higher technology readiness are more capable of converting purchase intentions into actual purchases. The model demonstrates acceptable explanatory power, and the IPMA analysis results also emphasize that purchase intention, trust, and technology readiness are key factors in increasing consumer acceptance of live streaming shopping. This study theoretically integrates the perspectives of technology and social interaction into the emerging digital retail environment, providing actionable insights for platforms and retailers aiming to enhance user engagement, reduce friction, and promote the adoption of live streaming.

Keywords: Live-streaming Shopping, Consumer, Behavior, Technology Readiness, Interactivity, Trust, PLS-SEM
JEL Classifications: M31, D12, O33

1. INTRODUCTION

Live-stream shopping has become one of the most influential forms of online retail, transforming how consumers evaluate products, interact with sellers, and make purchasing decisions. In China, online retail sales reached RMB 15.97 trillion in 2025, with new consumption formats and models such as live-streaming e-commerce and instant retail experiencing rapid growth. The live-streaming e-commerce industry maintained a strong growth momentum, with transaction volume increasing by 11.3% year-on-year in 2025, reflecting its growing importance in the digital economy (State Council of the People's Republic of China, 2026). Academic research indicates that live-stream e-commerce reshapes consumer perception through real-time social interaction, instant participation, and rich media presentation, thereby increasing user engagement and conversion rates (Wang & Wu, 2019; Yu et al,. 2025). Therefore, understanding the drivers of consumer intentions and actual behaviors in live-stream e-commerce has become a key topic in contemporary marketing and information systems research.

A significant characteristic that distinguishes live-stream shopping from traditional online shopping is its interactivity with customers. Real-time comments, feedback, and synchronous interaction significantly enhance consumer engagement, thereby strengthening their purchase intentions (Liu and Zhang, 2024). Ma (2023) points out that live-stream interactivity helps consumers reduce information asymmetry, instantly understand product details, and co-create the

consumption experience with the host and other consumers (Guo et al., 2021). Empirical research shows that interactivity is one of the strongest predictors of consumer engagement and trust in the live-stream shopping environment (Liu and Zhang, 2024).

Another key determinant of live-stream shopping is the credibility of the host. They simultaneously act as product presenters and provide consumers with advice; therefore, the host's credibility—including professionalism, credibility, and authenticity—is crucial in influencing purchasing decisions (Chen and Yang, 2023; Long et al., 2024). Research shows that the higher the credibility of the live-stream host, the lower the perceived risk for consumers, and the higher their trust, thus enhancing their willingness to purchase recommended products (Wongkitrungrueng and Assarut, 2020). Recent research further indicates that credibility not only affects cognitive evaluation but also influences emotional connection in quasi-social relationships, especially in the live-stream shopping environment (Chen and Yang, 2023). If consumers perceive live shopping as complex, their intention to use it will be significantly reduced. Complexity reflects consumers' perception of the ease of learning or operating an system or platform, which has been identified as an obstacle in the literature on the popularization of online shopping (Faiz et al., 2024). In live shopping—where rapid interaction, information overload, and unfamiliar interface features are common—complexity has been shown to increase cognitive load and reduce consumers' purchase intention (Zhang et al., 2023). Research shows that consumers experiencing live shopping for the first time may find it difficult to process content due to real-time promotions, multiple visual cues, and rapid information flow, all of which reduce their willingness to use live shopping (Ye et al., 2023; Zhang et al., 2023). However, despite the significant impact of perceived complexity, this issue remains under-researched in the field of real-time commerce, constituting a significant research gap.

While behavioral intention is widely considered the most direct predictor of actual behavior in technology use, research suggests that the link between intention and behavior may not always be strong in situations requiring real-time interaction or technical proficiency (Jeyaraj et al., 2026; Liu and Zhang, 2024). Researchers argue that user-level characteristics, such as technological readiness, may influence whether intention is successfully translated into actual use (Peng and Yan, 2022; Tennakoon, 2024). Technological readiness reflects an individual's propensity to accept and use new technologies (Godoe and Johansen, 2012). Emerging evidence suggests that consumers with high technological readiness are more capable of utilizing the complex features of live-streaming platforms, thereby increasing the likelihood of their intention translating into actual behavior (Faiz et al., 2024). However, few studies have explored the moderating role of technological readiness in live-streaming shopping, creating a significant research gap.

Therefore, this study draws upon the Technology Acceptance Model (TAM) and the Technology Readiness Model (TR) to construct a comprehensive model that integrates livestream interactivity, streamer credibility, perceived complexity (negative), intention, actual behavior, and technology readiness as a moderating variable. Through empirical testing of this model, this study aims to deepen the theoretical understanding of livestream e-commerce applications and provide actionable insights for practitioners who wish to improve user conversion rates through highly interactive and technologically advanced retail environments.

2. LITERATURE REVIEW

2.1. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) (Davis, 1989) is one of the most widely applied frameworks for explaining technology adoption (Venkatesh and Davis, 2000).TAM proposes that external system characteristics influence user intention primarily through perceived usefulness and perceived ease of use (Venkatesh and Bala, 2008).In the context of live-streaming commerce, many platform features—such as real-time interaction, information cues, and anchor communication—are considered external stimuli that shape users' cognitive evaluations and intentions (Ma, 2023).

2.2. Technology Readiness (TR) and TRAM Model

Technology readiness refers to individuals' propensity to adopt and use new technologies (Parasuraman and Colby, 2015). It reflects psychological drivers of adoption, including optimism, innovativeness, discomfort, and insecurity. Later research combined TRI with TAM to form the Technology Readiness and Acceptance Model (TRAM), which proposes that TR shapes how individuals form intentions and how effectively they translate intentions into actual behavior (Lin et al., 2007; Peng et al., 2022).In livestream commerce, higher readiness enables users to navigate rapid interactions, dynamic interfaces, and multitasking information environments, thereby making it easier to convert intention into actual behavior (Tennakoon, 2024). Conversely, low readiness may weaken the intention–behavior link.

2.3. Live Streaming Interactivity

Interactivity refers to the ability of users to actively participate in communication, exchange information, and receive feedback in real time (Liu and Shrum, 2002; Ma, 2023). In live streaming e-commerce, interactivity is significantly higher than in traditional e-commerce because consumers can ask questions, post comments, and immediately receive responses from the host and other viewers (Joo and Yang, 2023; Bolun et al, 2025). High interactivity can reduce information asymmetry and enhance consumers' sense of control and participation (Xu et al, 2022; Bolun et al, 2025). Research shows that interactivity is positively correlated with trust formation in digital commerce environments because real-time dialogue can enhance consumers' perception of transparency and authenticity (Ali et al, 2025). Furthermore, interactive features can enhance consumers' willingness to continue using live streaming platforms, making the shopping experience more immersive and socially interactive (Huang and Benyoucef, 2017). Therefore, we propose the following hypothesis:

H_1: Live streaming interactivity has a positive impact on trust.

H_2: Live streaming interactivity has a positive impact on the intention to use live streaming shopping.

2.4. Credibility of the Anchor

Anchor credibility refers to consumers' perception of the anchor's trust, professionalism, and authenticity (Ohanian, 1990). In live-

streaming e-commerce, anchors simultaneously play multiple roles—product demonstrator, entertainment anchor, and opinion leader—making their credibility crucial to consumers' decision-making (Zhang et al., 2022; Chen and Yang, 2023). Empirical research shows that credible anchors can reduce consumers' perceived risk and enhance trust by providing diagnostic product clues and authentic demonstrations (Wongkitrungrueng and Assarut, 2020). Recent research further indicates that anchor credibility can strengthen quasi-social relationships, thereby enhancing consumers' emotional attachment and trust in the anchor and platform (Wu and Chen, 2025). As quasi-social relationships deepen, consumers are more likely to adopt recommendations and exhibit stronger purchase intentions (Lee and Watkins, 2016). Therefore, we propose the following hypothesis:

H_3: Credibility of the anchor has a positive impact on trust.

H_4: Credibility of the anchor has a positive impact on the intention to use live streaming shopping.

2.5. Perceived Complexity

Perceived complexity refers to the degree to which users perceive a system as difficult to understand or use (Rogers, 2003). Complexity is a major obstacle to technology adoption because users with excessive cognitive load tend to avoid the system (Venkatesh et al., 2003). In live-streaming e-commerce, the fast pace of real-time information, multiple visual cues, limited-time offers, and unfamiliar interface functions all increase users' cognitive burden (Ali et al., 2025). Research shows that the higher the perceived complexity, the less confident users are in their ability to evaluate information and make informed decisions (Davis, 1989; Duong et al., 2022). Furthermore, complex interactive environments reduce users' willingness to participate, especially among consumers with less technological experience (Joo and Yang, 2023). Therefore, we propose the following hypotheses:

H_5: Perceived complexity has a negative impact on trust.

H_6: Perceived complexity has a negative impact on intention to use live streaming shopping.

2.6. Trust as a Mediating Factor

Trust is a core psychological mechanism in online commerce, reflecting users' beliefs about the reliability, integrity, and goodwill of platforms and participants (McKnight et al., 2002). In live-streaming environments, trust bridges the gap between persuasive cues (interactivity, credibility, complexity) and behavioral outcomes (Shih et al., 2024; Jiang et al., 2025). Trust increases when consumers perceive the environment as engaging and the streamer as trustworthy, thereby reducing concerns about fraud or misinformation (Li et al., 2023; Duong et al., 2025). Conversely, complexity increases uncertainty and cognitive stress, thus decreasing trust (Zhou et al., 2017; Men et al., 2024). Existing research consistently demonstrates that trust can predict purchase intentions and actual purchasing behavior in digital commerce (Gefen et al., 2003; Hajli, 2015; Handoyo, 2024). Therefore, we propose the following three mediation hypotheses:

H_7: Trust has a positive impact on actual purchasing behavior.

H_9: Trust mediates the relationship between interactivity and actual behavior.

H_{10}: Trust mediates the relationship between the credibility of the anchor and actual behavior.

H_{11}: Trust mediates the relationship between perceived complexity and actual behavior.

2.7. Intention to Use Live Streaming Shopping

Consumer intention has long been considered the strongest predictor of actual behavior (Ajzen, 1991). In the technology and e-commerce sectors, intention reflects consumers' intention to actively participate in a system (Venkatesh et al., 2003; Sun and Yu., 2025). In live-streaming e-commerce, intention is typically influenced by experiential value, interactivity, trust, and perceived information content (Wu and Huang, 2023; Shang et al., 2023). Empirical research shows that intention can effectively predict repeat use, purchase behavior, and platform loyalty (Wu and Huang, 2023; Bao and Zhu, 2023). Therefore, we propose the following hypothesis:

H_8: Intention to use live-streaming e-commerce has a positive impact on actual behavior.

2.8. Technology Readiness as a Moderator

Technology readiness (TR) captures an individual's tendency to adopt and use new technologies (Parasuraman and Colby, 2015). Individuals high in Technology readiness exhibit optimism, innovativeness, and confidence in digital environments, leading them to embrace interactive features more easily (Mahmood et al., 2023). Research shows that Technology readiness moderates the intention–behavior link, where high-TR consumers are more capable of translating positive intentions into real adoption or purchase actions (Na et al., 2021; Hoque et al., 2025). In fast-paced digital environments such as live-streaming commerce, Technology readiness is particularly salient, as it influences consumers' ability to handle information overload and complex interfaces (Chang and Chen, 2021). Thus, we propose:

H_{12}: Technology readiness positively moderates the relationship between intention to use live streaming and actual behavior.

3. RESEARCH METHODOLOGY

3.1. Measurement

Live interactiveness was measured using items adapted from Liu and Shrum (2002), designed to capture the level of real-time interaction perceived by users during live shopping. Credibility of the anchor was assessed using items derived from Ohanian (1990)'s endorser credibility scale and refined based on live shopping research (Wongkitrungrueng and Assarut, 2020), covering perceived credibility, professionalism, and authenticity. Perceived complexity was operationalized using items adapted from Rogers (2003) and Venkatesh et al. (2003), reflecting the perceived difficulty and cognitive effort required during live shopping. Trust in live shopping was measured using items adapted from McKnight et al. (2002) and Gefen et al. (2003), designed to understand consumers' perceptions of the reliability and integrity of live transactions. Willingness to use live-stream e-commerce was measured using items adapted from Ajzen (1991) and Venkatesh et al. (2003), reflecting consumers' future plans to use live-stream shopping. Actual behavior was assessed using items adapted from Chen et al. (2021) and Hajli (2015), evaluating consumers' actual

purchasing behavior in a live-stream environment. Technological readiness (a moderating variable) was assessed using items adapted from the Technological Readiness Index (Parasuraman and Colby, 2015), focusing on optimism and innovativeness. Figure 1 illustrates the conceptual framework of this study, which integrates perceived value dimensions and social presence interaction to explain consumers' intention to use live streaming shopping and their actual behavior.

3.2. Data Collection and Sampling

This study collected data from July to September 2025 to explore Chinese consumers' willingness to use live-stream shopping. The increasing number of live-stream hosts and retailers selling goods through live-streaming provides a strong background for this study. The target population was consumers in China who had used live-stream shopping platforms. The online questionnaire was distributed through the well-known Chinese survey platform "Wenjuanxing." To improve sample representativeness, a random sampling method was used to attract participants with diverse backgrounds and experiences. The questionnaire consisted of three parts. The first part introduced the research purpose, ensured user privacy, and explained the concept of live-stream shopping. The second part was a screening question used to identify eligible users—consumers residing in China, aged 18 or older, and who had used live-stream shopping. Only eligible users could complete the third part of the questionnaire. The third part collected users' personal information, including gender, age, income, and education level.

Determining the sample size involves factors such as research complexity, significance level, effect size, and statistical power, requiring at least 280 participants (Hair, 2014). We identified participants with live-stream shopping experience through a screening question ("Have you ever used live-stream shopping before?"). Consumers who had never used live-stream shopping were excluded from the study. Of the 300 questionnaires received, after removing incomplete or illogical answers and those completed online in <1 min, 284 valid questionnaires remained. Table 1 shows the sample characteristics. Women are the main user group for live-stream shopping. People aged 18-25 actively participate in live-stream e-commerce. University students account for 39.5%, and students make up 52.1% of all participants.

Table 1: Respondent demographics

Demographic variable	Classifications	Frequency	Percentage
Gender	Male	133	46.8
	Female	151	53.2
Age	18-25 years old	112	39.5
	26-30 years old	24	8.5
	31-35 years old	84	29.6
	36-40 years old	39	13.7
	Above 40 years old	25	8.8
Occupation	Student	148	52.1
	Corporate staff	27	9.5
	Professional	27	9.5
	Freelance	7	2.5
	Civil servants	47	16.5
	Other (please fill in)	28	9.9
Education	High school and below	15	5.3
	Junior college	153	53.9
	Undergraduate	81	28.5
	Postgraduate (e.g. Master/PhD)	35	12.3
Income	Below 3000￥	66	16.2
	3000.01-5000￥	114	28.0
	5000.01-7000￥	107	26.3
	7000.01-9000￥	73	17.9
	Above 9000￥	47	11.5

3.3. Common Method Bias

Because all variables in this study were measured using self-reported data collected from the same respondents, potential common method bias (CMB) was carefully examined, CMB = 25.762%. First, we adopted several procedural remedies during questionnaire design and data collection, including ensuring respondent anonymity, and separating measurement blocks to reduce evaluation apprehension and consistency motifs (Podsakoff et al., 2003).

Second, we assessed CMB using a full collinearity approach in PLS-SEM. Variance inflation factor (VIF) values for all latent constructs were below the conservative cutoff of 3.3, demonstrating the absence of pathological collinearity and indicating that the model is free from substantial CMB (Kock, 2015). This method is considered appropriate for PLS-SEM because it simultaneously captures vertical and lateral collinearity, providing a more stringent assessment than traditional techniques.

4. DATA COLLECTION AND SAMPLE PROFILE

4.1. Data Screening

This study employed SmartPLS 4.1 to evaluate the reflective measurement model following the established PLS-SEM guidelines (Hair et al., 2021). Internal consistency reliability was first assessed using Cronbach's alpha and composite reliability (CR). As presented in Table 2, all Cronbach's alpha values exceeded the recommended threshold of 0.70 (Nunnally and Bernstein, 1994), falling between 0.800 and 0.899. Similarly, CR values ranged from 0.881 to 0.930, surpassing the conservative benchmark of 0.70 and indicating satisfactory internal consistency (Hair et al., 2021). These results suggest that all constructs exhibit high measurement reliability.

Convergent validity was examined through indicator loadings and average variance extracted (AVE). All standardized loadings were above 0.740 and statistically significant, meeting the recommended minimum level of 0.70 (Hair et al., 2022). Additionally, AVE values ranged from 0.691 to 0.768, well above the suggested cutoff of 0.50 (Fornell and Larcker, 1981), demonstrating that each construct explains a substantial proportion of variance in its indicators. These results confirm that the measurement model exhibits strong convergent validity.

The reliability and validity diagnostics confirm that all reflective constructs meet or exceed the standards commonly accepted in high-quality empirical research. Therefore, the measurement

model is considered statistically sound and appropriate for subsequent evaluation of the structural model.

4.2. Discriminant Validity

Discriminant validity was assessed using two complementary criteria: the Heterotrait–Monotrait ratio (HTMT) and the Fornell–Larcker criterion. Following the recommendations of Henseler et al. (2015), HTMT was first examined as a more reliable and stringent indicator of discriminant validity in variance-based SEM. As reported in Table 3, all HTMT values were substantially below the conservative threshold of 0.85, indicating that each pair of constructs is empirically distinct. These results provide strong evidence that the latent variables capture unique conceptual domains and are not conflated with one another.

Table 2: Item loadings and reliability measures

Constructs	Items	Loadings	CR	AVE	Cronbach's α
Live Streaming Interactivity	LSI1	0.821	0.883	0.716	0.803
	LSI 2	0.821			
	LSI 3	0.821			
Credibility of the anchor	CA1	0.838	0.881	0.712	0.800
	CA2	0.864			
	CA3	0.829			
Perceived Complexity	PC1	0.871	0.898	0.746	0.831
	PC2	0.852			
	PC3	0.868			
Trust	TRU1	0.830	0.899	0.691	851
	TRU2	0.840			
	TRU3	0.825			
	TRU4	0.831			
Intention to use Live Streaming	INT1	0.74	0.930	0.768	0.899
	INT2	0.868			
	INT3	0.884			
	INT4	8.878			
Actual Behavior	AB1	0.854	0.903	0.698	0.856
	AB2	0.841			
	AB3	0.822			
	AB4	0.825			
Technology Readiness	TR1	0.831	0.906	0.707	0.867
	TR2	0.860			
	TR3	0.782			
	TR4	0.887			

Table 3: Heterotrait-Monotrait (HTMT) matrix

	AB	CA	INT	LSI	PC	TR	TRU	TR ×INT
AB								
CA	0.132							
INT	0.55	0.291						
LSI	0.171	0.081	0.324					
PC	0.255	0.058	0.376	0.067				
TR	0.191	0.075	0.044	0.074	0.128			
TRU	0.473	0.314	0.582	0.25	0.36	0.084		
TR x INT	0.169	0.047	0.027	0.047	0.03	0.074	0.048	

To further validate discriminant validity, the Fornell–Larcker criterion was applied (Fornell and Larcker, 1981). As displayed in Table 4, the square roots of the AVE values (shown on the diagonal) were greater than the corresponding inter-construct correlations. This condition was consistently satisfied across all constructs, suggesting that each construct explains more variance in its own indicators than in those of other constructs. The pattern of results confirms adequate separation between constructs within the measurement space.

Both the HTMT analysis and the Fornell–Larcker criterion provide convergent evidence for satisfactory discriminant validity. These findings verify that the constructs are statistically and conceptually distinct, ensuring that the measurement model is robust and appropriate for evaluating the structural relationships proposed in this study.

4.3. Structural Model and Hypothesis Testing

The structural model results derived from the PLS-SEM analysis are illustrated in Figure 2. The structural model was evaluated by examining collinearity, path coefficients, effect sizes, and statistical significance. As shown in Table 5, all inner VIF values ranged from 1.001 to 1.360, substantially below the conservative threshold of 3.3 (Kock, 2015), indicating the absence of multicollinearity among predictor constructs. Therefore, collinearity does not bias the estimation of structural relationships.

Regarding the hypothesized relationships, all path coefficients (β) were statistically significant and in the expected directions. Specifically, Credibility of the Anchor (CA) exerted significant positive effects on both Intention to Use Live Streaming (INT) ($\beta = 0.241$, $t = 5.013$, $P < 0.001$) and Trust (TRU) ($\beta = 0.252$, $t = 4.852$, $P < 0.001$). Live Streaming Interactivity (LSI) also had significant positive influences on INT ($\beta = 0.258$, $t = 4.776$, $P < 0.001$) and TRU ($\beta = 0.189$, $t = 3.579$, $P < 0.001$).

Table 4: Fornell-Larcker criterion

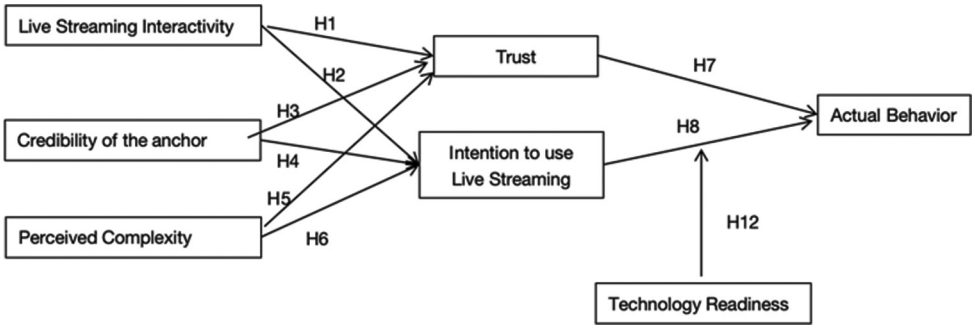
	AB	CA	INT	LSI	PC	TR	TRU
AB	0.836						
CA	0.108	0.844					
INT	0.486	0.253	0.876				
LSI	0.143	0.013	0.278	0.846			
PC	−0.216	−0.03	−0.326	−0.057	0.864		
TR	0.182	0.037	0.032	−0.033	−0.104	0.841	
TRU	0.406	0.264	0.509	0.209	−0.308	0.065	0.831

Table 5: Hypothesis testing

Path →	β	VIF	f^2	T-value	P-values	Supported
CA→INT	0.241	1.001	0.076	5.013	0.000	Yes***
CA→TRU	0.252	1.001	0.079	4.852	0.000	Yes***
INT→AB	0.368	1.353	0.147	7.367	0.000	Yes***
LSI→INT	0.258	1.003	0.086	4.776	0.000	Yes***
LSI→TRU	0.189	1.003	0.044	3.579	0.000	Yes***
PC→INT	-0.304	1.004	0.12	5.981	0.000	Yes***
PC→TRU	-0.289	1.004	0.103	5.492	0.000	Yes***
TR→AB	0.149	1.007	0.032	3.418	0.001	Yes**
TRU→AB	0.215	1.36	0.05	4.011	0.000	Yes***
TR×INT→AB	0.151	1.007	0.032	3.061	0.002	Yes**

Significance levels: *P<0.05; **P<0.01; ***P<0.001; two-tailed probabilities

Figure 1: Research framework



Conversely, Perceived Complexity (PC) showed significant negative effects on INT (β = −0.304, t = 5.981, P < 0.001) and TRU (β = –0.289, t = 5.492, P < 0.001), confirming that higher perceived complexity reduces users' confidence and intention to engage in live streaming commerce. In predicting Actual Behavior (AB), both Trust (β = 0.215, t = 4.011, P < 0.001) and Intention to Use Live Streaming (β = 0.368, t = 7.367, P < 0.001) demonstrated strong and significant positive effects, highlighting their importance as proximal determinants of behavioral outcomes. Technology Readiness (TR) also directly influenced AB (β = 0.149, t = 3.418, P = 0.001), suggesting that users with higher readiness toward emerging technologies are more likely to convert intention into actual usage. The interaction term TR × INT exhibited a significant moderating effect on AB (β = 0.151, t = 3.061, P = 0.002), indicating that the relationship between intention and behavior is amplified when users possess higher technology readiness. This finding provides empirical support for the theorized moderating role of TR.

Effect size analysis (f^2) further corroborates these results. INT had a moderate effect on AB (f^2 = 0.147), while TRU and TR demonstrated small yet meaningful effects (f^2 = 0.050 and 0.032, respectively). Predictors of INT and TRU also exhibited small-to-moderate f^2 values (0.044-0.120), aligning with Cohen's (1988) guidelines.

The structural model results confirm that the proposed relationships are statistically robust and theoretically consistent. All hypotheses were supported, indicating strong empirical evidence for the conceptual framework of live streaming shopping adoption.

The explanatory power of the structural model was examined using the R-square (R^2) values of the endogenous constructs, as shown in Table 6. The R^2 value for Actual Behavior was 0.317, indicating that the combined effects of Intention, Trust, and the intention to use live streaming shopping explain approximately 31.7% of the variance in users' actual adoption behavior. According to the guidelines proposed by Chin (1998), this represents a moderate level of explanatory power. The R^2 value for Intention to Use Live Streaming was 0.232, meaning that Credibility of the Anchor, Live Streaming Interactivity, and Perceived Complexity collectively account for 23.2% of the variance in users' behavioral intention. This falls within the range of weak-to-moderate explanatory power, which is commonly observed in technology adoption research where behavioral intention is influenced by diverse

Figure 2: Results of path analysis

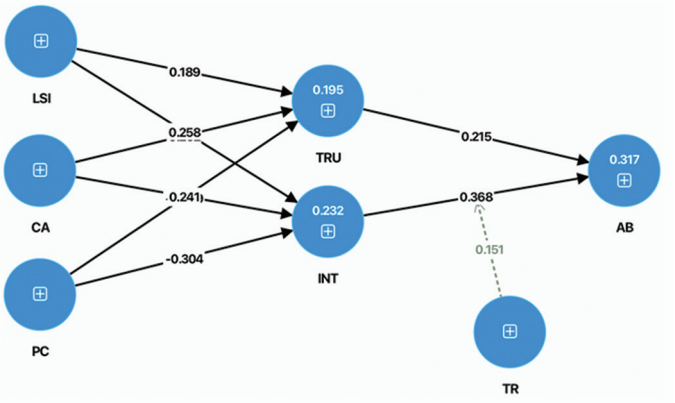


Table 6: R-square

AB	0.317
INT	0.232
TRU	0.195

individual and contextual factors. Trust yielded an R^2 of 0.195, suggesting that CA, LSI, and PC explain 19.5% of its variance. Although this represents a modest level of explanatory power, such values are considered acceptable in PLS-SEM when modeling complex socio-psychological constructs (Hair et al., 2019).

These R^2 values indicate that the proposed model exhibits acceptable predictive accuracy and is sufficiently robust for hypothesis testing. Despite the presence of moderate explanatory power only for AB, the results are consistent with prior behavioral and technology adoption studies, where psychological outcomes often demonstrate modest levels of explained variance.

4.4. Importance–performance Map Analysis

The importance–performance map analysis (IPMA) was conducted to provide deeper managerial insights by jointly considering the effects (importance) and performance levels of each antecedent of Actual Behavior (AB). Table 7 and Figure 3 summarize the IPMA results. Consistent with the recommendations of Hair et al. (2019), importance was measured using total effects, while performance scores were derived from the rescaled latent variable scores (0-100 scale).

First, Intention to Use Live Streaming Shopping (INT) exhibits the highest importance (β = 0.368) but shows only moderate

Figure 3: Importance-performance map analysis

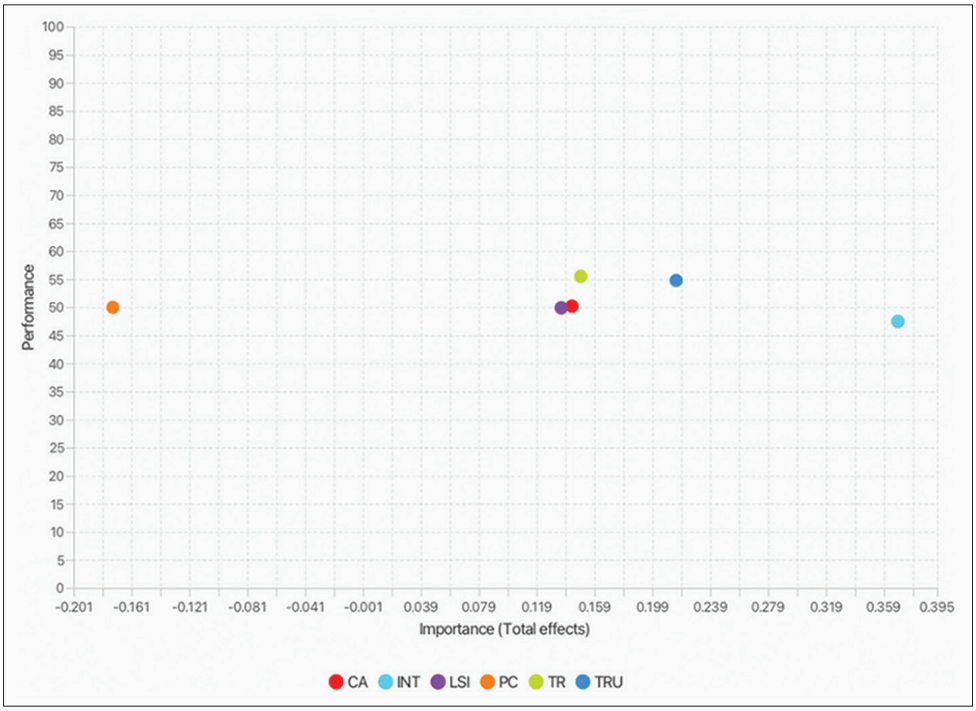


Table 7: IPMA on actual behavior

Variables	Importance	Performance
Credibility of the anchor (CA)	0.143	50.191
Intention to use Live Streaming Shopping (INT)	0.368	47.463
Live Streaming Interactivity (LSI)	0.136	49.891
Perceived Complexity (PC)	−0.174	49.97
Technology Readiness (TR)	0.149	55.505
Trust (TRU)	0.215	54.773

performance (47.463). This suggests that consumers' actual use of live-streaming shopping is strongly driven by their intention; however, the intention level is not yet high. Therefore, practitioners should prioritize strategies that strengthen users' willingness to adopt live-streaming shopping—such as enhancing user experience, reducing perceived uncertainty, and increasing motivational cues. Second, Trust (TRU) demonstrates a notable level of importance (β = 0.215) and relatively high performance (54.773). Although trust already performs well, further improvements—such as enhancing platform security, ensuring transparency, and strengthening credibility—can yield additional behavioral gains due to its substantive explanatory power.Third, Technology Readiness (TR) also shows a meaningful impact (β = 0.149) and the highest performance score (55.505). This implies that users in the sample generally possess a strong readiness to adopt new technologies. For platform providers, leveraging this advantage through more innovative features, seamless interfaces, and personalized services may further reinforce adoption behavior.Fourth, Credibility of the Anchor (CA) and Live Streaming Interactivity (LSI) present moderate importance values (β = 0.143 and β = 0.136 respectively) with performance levels close to the midpoint (≈50). These findings highlight that enhancing anchor professionalism, communication quality, and interactive engagement can still generate notable behavioral improvements.Finally, Perceived Complexity (PC) displays a negative total effect (β = −0.174), indicating that reducing complexity is essential for increasing Actual Behavior. While its performance score is relatively average (49.97), lowering complexity through simpler interfaces and intuitive navigation can significantly reduce barriers to user adoption.

The IPMA results underscore that increasing intention and trust, while reducing system complexity, should be key strategic priorities for practitioners. By contrast, constructs such as technology readiness and trust already exhibit high performance, suggesting that maintaining (rather than radically improving) these dimensions may be sufficient.

5. CONCLUSION AND IMPLICATION

5.1. Conclusion

This study aims to explore the key psychological and technological drivers influencing consumers' intentions and actual behaviors in live-streaming shopping. Based on the Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh et al., 2003), Technology Readiness (TR) (Parasuraman and Colby, 2015), and contemporary live-streaming e-commerce literature (Sun et al., 2019; Wongkitrungrueng and Assarut, 2020), this study constructs and empirically validates a comprehensive model that integrates Live Streaming Interactivity, Credibility of the Anchor, Perceived Complexity, Trust, Intention to Use Live Streaming, and Actual Behavior, with Technology Readiness serving as a context-moderating variable.

This study used 284 valid questionnaires and SmartPLS 4.1 software to obtain some noteworthy findings. First, livestream interactivity and credibility were confirmed as strong and stable promoters of trust and purchase intention, further confirming previous findings that social presence and real-time interaction

are crucial for digital persuasion in livestream e-commerce (Sun et al., 2019; Lou and Yuan, 2019). Second, perceived complexity had a significant negative impact on trust and purchase intention, consistent with previous research that excessive cognitive load weakens technology adoption and user evaluation (Davis, 1989). Third, the study found that purchase intention and trust are strong predictors of actual behavior, consistent with long-standing behavioral models in online commerce (Gefen et al., 2003; Pavlou, 2003), highlighting the importance of psychological assurance in the fast-paced digital shopping environment.

Importantly, this study provides empirical evidence for the moderating effect of technological readiness. Higher consumer readiness leads to a greater ability to convert intention into actual purchase behavior, suggesting that digital capabilities can enhance the effectiveness of persuasion mechanisms in livestream shopping scenarios. This finding expands upon previous research, demonstrating that technological readiness remains a significant factor even in socially interactive and entertainment-driven business environments (Na et al., 2021; Hoque et al., 2025). The findings indicate that consumer acceptance of live-stream shopping is not influenced by a single factor, but rather by the combined effects of multiple factors, including interaction, cognition, and technology (Zhang et al., 2022). The proposed model demonstrates strong explanatory power and provides new empirical insights into how consumers move from initial contact to engagement and ultimately to actual purchases in live-stream e-commerce. As live-streaming becomes increasingly prevalent in the digital economy, these insights clarify which mechanisms platforms and retailers must optimize to sustain growth and improve conversion rates.

This study makes a meaningful theoretical and practical contribution by combining technology-driven structures with social drivers and validating the relationship using a robust partial least squares structural equation model (PLS-SEM) (Hair et al., 2019). The research also elucidates how consumers' psychological and technological readiness shapes their actual behavior in the rapidly evolving digital retail environment. Future research could further expand this model by applying it to product categories, platform types, and cultural contexts to deepen our understanding of live-streaming e-commerce behavior.

5.2. Theoretical Implications

This study provides several important theoretical implications for research in the fields of live-stream shopping platforms, technology adoption in live-stream shopping platforms, and interactive digital platforms. First, this study expands upon traditional technology adoption theory, demonstrating that concepts originally developed for general information systems—such as technology readiness (TR), trust, and perceived complexity—remain highly relevant in the socially interactive, entertainment-driven environment of live-stream shopping. However, this research shows that consumers' latent technological propensity plays a decisive role in shaping user intentions into actual usage behavior. This expands the theoretical boundaries of the TRAM-based framework and positions technology readiness as a crucial psychological resource in highly interactive digital commerce environments.

Second, this study empirically demonstrates that interactivity and anchor credibility jointly influence trust and confidence, thus advancing research in the field of live-stream shopping. Previous studies have often treated these factors independently, neglecting their synergistic effects. This study, by integrating social cues, interactive communication, and relational signals, constructs a single structural model demonstrating that these factors are the fundamental mechanisms by which consumers assess uncertainty and form purchase intentions in live-stream e-commerce. This expands our theoretical understanding of social presence and quasi-social interaction in real-time e-commerce environments.

Third, the significant negative impact of perceived complexity, by emphasizing the cognitive load brought about by the interface of live-streaming shopping platforms, enriches existing theories. While previous research has highlighted information overload or impulsive decision-making, few studies have systematically examined how system complexity hinders consumers' ability to process persuasive cues. This study finds that perceived complexity is a key inhibitor of trust and purchase intention, providing a more nuanced perspective on cognitive barriers in the fast-paced digital shopping environment.

Fourth, this study verifies the strong predictive power of trust and purchase intention on actual behavior in live-streaming environments, thus contributing to behavioral research. Although the relationship between intention and behavior has been well-established in classical behavioral theory, this study demonstrates that in highly dynamic and socialized purchasing environments, trust plays a crucial psychological bridging role, reducing perceived risk and enhancing behavioral activation. This provides empirical support for incorporating a trust-based perspective into explanatory models of real-time commercial behavior.

Furthermore, the introduction of Importance-Performance Map Analysis (IPMA) deepens the theory by clarifying that not all determinants contribute equally to actual behavior. By identifying intention, trust, and interactivity as high-importance components, this study reveals which psychological and technological levers have the greatest impact on actual adoption, thus advancing the theory and providing richer insights beyond traditional path coefficient explanations.

These contributions deepen the theoretical understanding of how consumers adapt to highly interactive digital business environments at cognitive, social, and technological levels. This research not only integrates multiple theoretical perspectives—the Technology Acceptance Model (TAM), Trust Theory (TR), Trust Theory, and the Interaction Framework—but also empirically validates their interactions in shaping real-world behavioral outcomes.

5.3. Managerial Implications

This study offers several practical recommendations for live-stream shopping platforms and online retailers. First, consumer willingness to use live-stream shopping has the most significant impact on actual behavior, but its effect remains moderate. Therefore, platforms should prioritize strategies to enhance

consumer intention, such as personalized recommendations, interactive activities, and reward mechanisms, to strengthen user engagement. Second, trust remains a key factor influencing behavioral outcomes. Improving platform transparency, strengthening seller vetting, enhancing product demonstration quality, and providing secure transaction guarantees can further enhance consumer trust. Third, the credibility and interactivity of live-stream hosts highlight the crucial role of communication and social cues. Retailers should provide professional training to live-stream hosts, ensuring they can interact and showcase products promptly. Fourth, perceived complexity has a significant negative impact, highlighting the critical importance of a simple interface for live-stream shopping platforms. Simplified navigation, reduced information overload, and user guidance (especially for consumers with lower levels of education) help reduce consumer friction, thereby promoting consumer acceptance of live-stream shopping.

The moderating effect of technological readiness suggests that tailoring the platform experience to different user groups, such as a version for older users, may improve conversion rates. Advanced features are geared towards users with high technical proficiency, while simplified versions benefit users with lower technical confidence.

5.4. Limitations and Future Research Directions

Although this study provides meaningful insights into consumer behavior in livestream shopping, several limitations should be acknowledged. First, the data were obtained through a cross-sectional survey, which restricts the ability to capture dynamic behavioral changes. Second, self-reported behavioral measures may be subject to bias. Third, the research model focused on selected psychological and technological drivers, and thus did not incorporate other potentially influential variables.

Building on these limitations, several promising directions can guide future research. To begin with, longitudinal or experimental designs could be employed to validate causal relationships and examine how consumers' trust, intention, and technology readiness evolve with platform usage. Future studies may also incorporate objective behavioral data—such as viewing time, clickstream logs, or actual purchase records—to complement self-reported measures.

Moreover, extending the model to different platform types (e.g., TikTok, Taobao Live, YouTube Live) or industry categories (e.g., beauty, electronics, fresh food) could reveal contextual variations in how interactivity, credibility, and complexity shape user responses. Cross-cultural comparisons would further clarify how cultural values influence trust formation and livestream adoption. Researchers may also diversify the theoretical lens by incorporating constructs such as perceived enjoyment, parasocial interaction, social presence, or algorithmic fairness to enrich the explanatory power of existing frameworks. Finally, more advanced segmentation techniques—for instance, clustering based on technology readiness or digital literacy—could help uncover heterogeneous consumer groups and provide a more nuanced understanding of their behavioral patterns.

REFERENCES

Ajzen, I. (1991), The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179-211.

Ali, F., Janjua, Q., Maqsood, H. (2025), The rise of live-streaming E-commerce: Analyzing consumer purchase behavior and brand trust in real-time shopping events. Journal of Management and Social Science, 2(1), 430-447.

Bao, Z., Zhu, Y. (2023), Understanding customers' stickiness of live streaming commerce platforms: An empirical study based on modified e-commerce system success model. Asia Pacific Journal of Marketing and Logistics, 35(3), 775-793.

Bolun, Z., Yan, Z., Minghui, J. (2025), The configurational impact of e-commerce live streaming interactivity on consumer engagement behavior. Asia Pacific Journal of Marketing and Logistics, 37(3), 631-649.

Chang, Y.W., Chen, J. (2021), What motivates customers to shop in smart shops? The impacts of smart technology and technology readiness. Journal of Retailing and Consumer Services, 58, 102325.

Chen, N., Yang, Y. (2023), The role of influencers in live streaming e-commerce: Influencer trust, attachment, and consumer purchase intention. Journal of Theoretical and Applied Electronic Commerce Research, 18(3), 1601-1618.

Chin, W.W. (1998), The partial least squares approach to structural equation modeling. In: Modern Methods for Business Research. United Kingdom: Psychology Press. p295-336.

Davis, F.D. (1989), Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13, 319-340.

Duong, N.T., Lin, H.H., Wu, T.L., Wang, Y.S. (2025), Understanding consumer trust dynamics and purchase intentions in a multichannel live streaming e-commerce context: A trust transfer perspective. International Journal of Human-Computer Interaction, 41(14), 9123-9136.

Faiz, F., Le, V., Masli, E.K. (2024), Determinants of digital technology adoption in innovative SMEs. Journal of Innovation and Knowledge, 9(4), 100610.

Fornell, C., Larcker, D.F. (1981), Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39-50.

Gefen, D., Karahanna, E., Straub, D.W. (2003), Trust and TAM in online shopping: An integrated model. MIS Quarterly, 27(1), 51-90.

Godoe, P., Johansen, T.S. (2012),Understanding adoption of new technologies: Technology readiness and technology acceptance as an integrated concept. Journal of European Psychology Students, 3(1), 38-52.

Guo, J., Li, Y., Xu, Y., Zeng, K. (2021), How live streaming features impact consumers' purchase intention in the context of cross-border E-commerce? A research based on SOR theory. Frontiers in Psychology, 12, 767876.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2014). A primer on partial least squares structural equation modeling (PLS-SEM). Thousand Oaks, CA: SAGE Publications.

Hair, J.F., Risher, J.J., Sarstedt, M., Ringle, C.M. (2019), When to use and how to report PLS-SEM results. European Business Review, 31(1), 2-24.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). SAGE Publications.

Hajli, N. (2025), Social commerce constructs and consumer's intention to buy. International Journal of Information Management, 35(2), 183-91.

Handoyo, S. (2024), Purchasing in the digital age: A meta-analytical perspective on trust, risk, security, and e-WOM in e-commerce.

Heliyon, 10(8), e29714.
Henseler, J., Ringle, C.M., Sarstedt, M. (2015), A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115-135.
Hoque, M.A., Mahmood, R., Ali, R., Rosli, N.S., Hossain, M.M. (2025), Drivers of AI adoption in banks in Bangladesh: The moderating role of technology readiness. ICRRD Journal, 6(4), 231-246.
Huang, Z., Benyoucef, M. (2017), The effects of social commerce design on consumer purchase decision-making: An empirical study. Electronic Commerce Research and Applications, 25, 40-58.
Jeyaraj, A., Rottman, J.W., Lacity, M.C. (2006), A review of the predictors, linkages, and biases in IT innovation adoption research. Journal of Information Technology, 21(1), 1-23.
Jiang, H.B., Fan, Z.Y., Wang, J.L., Liu, S.H., Lin, W.J. (2025), The determinants of product trust in live streaming E-commerce: A hybrid method integrating SEM and fsQCA. Asia Pacific Journal of Marketing and Logistics, 37(2), 273-293.
Joo, E., Yang, J. (2023), How perceived interactivity affects consumers' shopping intentions in live stream commerce: Roles of immersion, user gratification and product involvement. Journal of Research in Interactive Marketing, 17(5), 754-772.
Kock, N. (2015), Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration, 11(4), 1-10.
Lee, J.E., Watkins, B. (2016), YouTube vloggers' influence on consumer luxury brand perceptions and intentions. Journal of Business Research, 69(12), 5753-5760.
Li, Q., Zhao, C., Cheng, R. (2023), How the characteristics of live-streaming environment affect consumer purchase intention: The mediating role of presence and perceived trust. IEEE Access, 11, 123977-123988.
Li, W., Song, R., Yu, K. (2025), Consumer adoption of food blockchain traceability: Insights from integrating TAM and TR models. Frontiers in Sustainable Food Systems, 9, 1515188.
Lin, C.H., Shih, H.Y., Sher, P.J. (2007), Integrating technology readiness into technology acceptance: The TRAM model. Psychological Reports, 100(3), 707-721.
Liu, X., Zhang, L. (2024), Impacts of different interactive elements on consumers' purchase intention in live streaming e-commerce. PLoS One, 19(12), e0315731.
Liu, Y., Shrum, L.J. (2002), What is interactivity and is it always such a good thing? Implications of definition, person, and situation for the influence of interactivity on advertising effectiveness. Journal of Advertising, 31(4), 53-64.
Long, J., Zaidin, N., Mai, X. (2024), Social media influencer streamers and live-streaming shopping: Examining consumer behavioral intention through the lens of the theory of planned behavior. Future Business Journal, 10(1), 80.
Lou, C., Yuan, S. (2019), Influencer marketing: How message value and credibility affect consumer trust of branded content on social media. Journal of Interactive Advertising, 19(1), 58-73.
Ma, Y. (2023), Effects of interactivity affordance on user stickiness in livestream shopping: Identification and gratification as mediators. Heliyon, 9(1), e1217.
Mahmood, A., Imran, M., Adil, K. (2023), Modeling individual beliefs to transfigure technology readiness into technology acceptance in financial institutions. Sage Open, 13(1).
McKnight, D.H., Choudhury, V., Kacmar, C. (2002), Developing and validating trust measures for e-commerce: An integrative typology. Information Systems Research, 13(3), 334-359.
Men, J., Zheng, X., Davison, R.M. (2024), The role of vicarious learning strategies in consumers' uncertainty: The case of live-streaming shop**. Internet Research, 34(3), 891-916.
Na, T.K., Lee, S.H., Yang, J.Y. (2021), Moderating effect of gender on the relationship between technology readiness index and consumers' continuous use intention of self-service restaurant kiosks. Information, 12(7), 280.
Nunnally, J. C. (7). Bernstein, IH (1994). Psychometric theory. New York: McGraw Hill. Pandemic school closures in Switzerland. Int J Psychol, 56(4), 566-576.
Ohanian, R. (1990), Construction and validation of a scale to measure celebrity endorsers' perceived expertise, trustworthiness, and attractiveness. Journal of Advertising, 19(3), 39-52.
Parasuraman, A., Colby, C.L. (2015), Technology readiness index (TRI) 2.0. Journal of Service Research, 18(1), 59-74.
Pavlou, P.A. (2003), Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. International Journal of Electronic Commerce, 7(3), 101-134.
Peng, M.Y.P., Yan, X. (2022), Exploring the influence of determinants on behavior intention to use of multiple media kiosks through technology readiness and acceptance model. Frontiers in Psychology, 13, 852394.
Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y., Podsakoff, N.P. (2003), Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879.
Rogers, E.M. (2003), Diffusion of Innovations. 5th ed. Washington, DC: Free Press.
Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In Handbook of market research (pp. 587-632). Cham: Springer International Publishing.
Shang, Q., Ma, H., Wang, C., Gao, L. (2023), Effects of background fitting of e-commerce live streaming on consumers' purchase intentions: A cognitive-affective perspective. Psychology Research and Behavior Management, 16, 149-168.
Shih, I.T., Silalahi, A.D.K., Eunike, I.J. (2024), Engaging audiences in real-time: The nexus of socio-technical systems and trust transfer in live streaming e-commerce. Computers in Human Behavior Reports, 13, 100363.
Sun, C., Yu, C. (2025), Study on enhancing consumers' purchase intention in E-commerce agricultural products. British Food Journal, 127(6), 2015-2034.
Sun, Y., Shao, X., Li, X., Guo, Y., Nie, K. (2019), How live streaming influences purchase intentions in social commerce: An IT affordance perspective. Electronic Commerce Research and Applications, 37, 100886.
Tennakoon, I. (2024), Impact of technology readiness in digital banking adoption and role of mediating effect of behavioral intention: A study of commercial banking customers of Sri Lanka. Journal of Business and Technology, 8(2), 1-22.
The State Council The People's Republic of China. (2026, March). China's online retail market ranks first globally for 13 consecutive years, with online consumption continuing to improve.https://www.gov.cn/lianbo/202603/content_7060109.htm
Venkatesh, V., Bala, H. (2008), Technology acceptance model 3 and a research agenda on interventions. Decision Sciences, 39(2), 273-315.
Venkatesh, V., Davis, F.D. (2000), A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management Science, 46(2), 186-204.
Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D. (2003), User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425-478.
Wang, X., Wu, D. (2019), Understanding user engagement mechanisms on a live streaming platform. In: International Conference on Human-Computer Interaction. Cham: Springer International Publishing. p266-275.
Wongkitrungrueng, A., Assarut, N. (2020), The role of live streaming in building consumer trust and engagement with social commerce

sellers. Journal of Business Research, 117, 543-556.
Wu, H.L., Chen, T.Y. (2025), Using Instagram live-streaming viewers model to derive two types of needs satisfaction. Asia Pacific Journal of Marketing and Logistics, 37(5), 1384-1400.
Wu, Y., Huang, H. (2023), Influence of perceived value on consumers' continuous purchase intention in live-streaming e-commerce-mediated by consumer trust. Sustainability, 15(5), 4432.
Xu, P., Cui, B.J., Lyu, B. (2022), Influence of streamer's social capital on purchase intention in live streaming E-commerce. Frontiers in Psychology, 12, 748172.
Ye, X., Batool, H., Huang, S.Z. (2023), The effect of e-commerce livestreaming services on customer loyalty: A test of the chain mediation model. Journal of Innovation and Entrepreneurship, 12(1), 41.
Yu, T., Teoh, A. P., Liao, J., & Wang, C. (2025). How do virtual influencers drive impulsive buying behaviour in e-commerce live streaming: the effects of parasocial relationship and influencer-product fit. Behaviour & Information Technology, 1-31.
Zhang, G., Cao, J., Liu, D. (2023), Examining the influence of information overload on consumers' purchase in live streaming: A heuristic-systematic model perspective. PLoS One, 18(8), e0284466.
Zhang, S., Huang, C., Li, X., Ren, A. (2022), Characteristics and roles of streamers in e-commerce live streaming. The Service Industries Journal, 42(13-14), 1001-1029.
Zhou, J., Arshad, S.Z., Luo, S., Chen, F. (2017), Effects of uncertainty and cognitive load on user trust in predictive decision making. In: IFIP Conference on Human-Computer Interaction. Cham: Springer International Publishing. p23-39.