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Purchase Behavior in AI-Enabled Livestream Commerce: Evidence from an Emerging Economy

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Abstract

This study aims to examine consumer purchase behavior in AI-enabled livestream commerce as an emerging form of AI-driven digital commerce. Specifically, the research investigates how technological and social–psychological factors influence perceived ease of use, perceived usefulness, intention to use, and purchase behavior. Data were collected through an online survey using convenience and snowball sampling methods, resulting in 248 valid responses. Partial least squares structural equation modeling (PLS-SEM) was employed to analyze the proposed relationships. The findings indicate that compatibility and self-satisfaction positively influence both perceived ease of use and perceived usefulness, while perceived risk negatively affects these perceptions. Social influence significantly enhances perceived usefulness but does not have a significant effect on perceived ease of use. In addition, perceived ease of use and perceived usefulness significantly strengthen intention to use, which subsequently drives purchase behavior. This study contributes to the literature by extending the TAM–UTAUT framework within the context of AI-enabled livestream commerce and by offering new insights into how AI streamers reshape consumer–platform interactions. These findings provide both theoretical contributions and practical implications for AI-driven commerce in emerging markets.

Keywords:

Artificial Intelligence;
Livestream Commerce;
Purchase Behavior;
Technology Adoption;
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1- Introduction

The rapid development of artificial intelligence (AI), along with immersive technologies such as virtual reality (VR) and augmented reality (AR), is significantly reshaping the landscape of consumer shopping behavior worldwide [1]. Within this evolving digital environment, AI-powered virtual streamers have emerged as a novel form of interaction, offering continuous availability, scalability, and cost efficiency in livestream commerce settings [2]. While these AI-driven agents demonstrate strong capabilities in delivering consistent information and supporting automated interactions, their effectiveness in translating technological capabilities into actual consumer purchase behavior remains uncertain [3]. In traditional livestream commerce, human streamers rely heavily on emotional expression, social presence, and real-time engagement to influence consumers' decisions [4]. In contrast, AI streamers operate through algorithm-driven interactions, emphasizing informational accuracy, personalization, and operational consistency [4]. Consequently, the success of AI-enabled livestream commerce depends not only on technological sophistication but also on how consumers perceive, interpret, and respond to these AI-mediated interactions [3, 5]. This shift raises important questions regarding how consumers evaluate and trust AI-driven interactions in commerce environments.

Empirical research on AI streamers, particularly within the Vietnamese context, remains limited [2]. To address this gap, this study adopts an extended TAM–UTAUT framework to examine how technological perceptions, such as perceived usefulness and perceived ease of use, interact with social–psychological factors, including perceived risk

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and compatibility, in shaping consumer behavior [6]. Recent studies have increasingly explored the role of AI in influencing consumer interactions and decision-making processes in digital commerce settings [7-10]. Building on this stream of research, the present study argues that both informational and social interaction mechanisms jointly shape consumers' perceptions, which subsequently influence their intention to use and purchase through AI-enabled livestream platforms [3].

Despite the growing body of research on livestream commerce and AI applications, limited studies have systematically examined how AI streamers differ from human streamers in shaping consumer trust and behavioral responses, particularly in emerging markets [5, 7, 11]. Existing research primarily focuses on human-led livestream environments or treats AI as a technological tool without fully addressing its distinct interaction mechanisms. Nonetheless, prior studies often apply the TAM or the UTAUT independently, without integrating technological and social-psychological factors within a unified analytical framework [12, 13]. Therefore, this study addresses these gaps by developing an extended TAM–UTAUT model to examine consumer purchase behavior in AI-enabled livestream commerce in Vietnam. This research contributes by bridging technological acceptance theories with AI-mediated interaction contexts, offering new insights into consumer behavior in emerging digital commerce ecosystems.

2- Literature Review and Research Model

2-1- Literature Review

Unlike human streamers, AI streamers rely on algorithm-driven interactions rather than authentic emotional expression [14, 15]. Human streamers typically influence consumers through emotional engagement, social presence, and real-time interpersonal communication, whereas AI streamers primarily shape consumer perceptions through informational efficiency, personalization, and consistency in content delivery [16]. This fundamental distinction suggests that trust in AI-enabled livestream commerce may be more cognitively driven, based on system reliability and performance, rather than emotionally driven as in human-led livestream environments [11, 17]. Live commerce combines real-time video streaming with online retail functions, allowing sellers to demonstrate products while interacting with consumers through live communication features [18]. As an e-commerce channel, live commerce has fundamentally reshaped consumer shopping preferences [19, 20]. Due to the impact of the COVID-19 pandemic, consumer demand for non-face-to-face (NFTF) commerce has surged rapidly [21]. However, compared to live commerce, traditional e-commerce still faces certain limitations particularly a lack of interactivity [22]. Live commerce, powered by real-time streaming technology, emerged to address this shortcoming [7]. Consumers can examine products, ask questions, and make purchasing decisions instantly while watching the live broadcast [6]. By leveraging high interactivity, entertainment elements, and the influence of streamers including celebrities, Internet icons, or virtual streamers, this format effectively engages customers and drives rapid purchasing behavior [22].

Artificial intelligence (AI) refers to the capability of computational systems to perform tasks that typically require human intelligence, including learning from data, recognizing patterns, and making decisions in complex environments [23]. As a subfield of computer science, AI focuses on developing software and technologies that allow machines to perceive their environment, learn from data, and act intelligently to achieve specific goals [5, 24]. Over the past few decades, AI has played an increasingly vital role in economics and finance, fostering interdisciplinary connections with data science [25], and continuing the trend of collaboration across technology, finance, and economics [26]. In education, AI facilitates personalized learning and enhances intelligent tutoring systems [27]. Within organizations, AI boosts productivity and efficiency while promoting cooperation between businesses, academia, and the government [28]. Notwithstanding, AI also faces significant limitations: high implementation and maintenance costs, potential technical errors, and concerns regarding human replacement or the loss of technological control [29]. In the educational sector, further research is needed on the role of teachers, student adaptability, and cost-effectiveness [27]. Meanwhile, organizational adoption is hindered by a shortage of skilled labor, high costs, and employee resistance [30]. AI virtual streamers are non-human "actors" driven by artificial intelligence programs to perform marketing tasks and promote products during live broadcast sessions [6]. These virtual characters possess the capability to automate repetitive tasks, interactively respond to consumers, and adapt to diverse scenarios [14]. However, a significant limitation of AI virtual streamers is their lingering lack of natural, human-like emotional expression [15]. Their interactive behaviors such as voice, gestures, and facial expressions are often simulated, remaining rigid compared to real humans. Consequently, establishing a genuine emotional connection with consumers remains more restricted and challenging than it is for human streamers [6, 16, 31].

The Technology Acceptance Model (TAM), originally proposed by Davis [32], is widely used to explain and predict users' acceptance of new technologies. TAM explains technology adoption through two key perceptions, usefulness and ease of use, which shape users' behavioral intention and subsequent system usage [32, 33]. Perceived usefulness refers to the extent to which an individual believes that using a particular system will enhance their performance, while perceived ease of use reflects the degree to which using the system is perceived as effortless [34]. These perceptions jointly influence users' attitudes and behavioral intentions, which ultimately lead to actual system usage [32-34]. To provide a more comprehensive perspective, the Unified Theory of Acceptance and Use of Technology (UTAUT) extended TAM by incorporating additional determinants such as social influence and facilitating conditions [12], integrating multiple theoretical perspectives to provide a more comprehensive explanation of technology adoption. UTAUT emphasizes the role of social influence and facilitating conditions, in addition to performance expectancy and effort expectancy, in shaping behavioral intention and usage behavior [12, 13]. In contemporary digital environments, particularly AI-enabled platforms, consumer decisions are not solely driven by technological perceptions but are also influenced by social and psychological factors. Hence, integrating TAM and UTAUT provides a more holistic framework for understanding consumer behavior in AI-enabled livestream commerce, where both technological functionality and social interaction jointly shape user acceptance and purchase behavior. This integration is particularly relevant in emerging markets, where both technological readiness and social influence jointly shape adoption behavior.

2-2- Related Works

Perceived risk and social influence are consistently highlighted as critical determinants shaping consumer perceptions and behavioral responses in AI-enabled livestream commerce [6, 7]. High levels of perceived risk tend to undermine trust and reduce favorable evaluations, whereas social influence can enhance perceived ease of use and usefulness by reinforcing normative acceptance and reducing uncertainty through perceived risk mitigation mechanisms [11, 17, 35]. Compatibility has also been recognized as a key antecedent, as alignment between AI-enabled livestream features and consumers' shopping habits strengthens both cognitive and affective responses [36]. System stimulation and interactivity are widely examined as drivers of user engagement and positive evaluations in livestream commerce environments [5-7]. Prior studies suggest that immersive and responsive livestream settings enhance perceived usefulness and encourage sustained interaction with AI-driven streamers [37]. However, the magnitude of these effects appears to vary across cultural and technological contexts, raising concerns regarding their generalizability [38].

Perceived ease of use and perceived usefulness play mediating roles between AI-enabled livestream characteristics and consumers' purchase intentions [6]. When consumers perceive livestream platforms as intuitive and beneficial, they are more likely to form favorable usage intentions and engage in purchasing behaviors [7, 12, 13]. Prior studies suggest that attitude serves as a critical mechanism translating cognitive evaluations into actual usage and purchase behavior [39], and AI-driven digital commerce application and information flows influence consumer purchasing behavior in online commerce contexts [40].

Despite growing scholarly attention, limited research has systematically examined how psychological and perceptual factors jointly influence purchase intention through technology acceptance mechanisms in AI-enabled livestream commerce, particularly in emerging markets. This study therefore re-examines the structural relationships among perceived risk, social influence, self-satisfaction, compatibility, perceived ease of use, perceived usefulness, and intention to use, providing empirical insights within the Vietnamese livestream commerce context.

2-3- Research Model

In the context of AI-enabled livestream commerce, TAM and UTAUT provide appropriate theoretical frameworks for explaining how consumers decide to use platforms integrated with AI streamers [34]. These models require further extension to capture the unique characteristics of livestream environments, where emotional responses, interactive experiences, and trust play roles that are equally important as technological considerations [5, 6, 7]. Drawing on the Technology Acceptance Model (TAM) and related consumer behavior theories, this study develops a research model that highlights four key antecedents Perceived risk (PRI), Social influence (SIN), Self-satisfaction (SSA), and Compatibility (COM) in shaping consumers' Perceived ease of use (PEU) and Perceived usefulness (PUS) toward AI-enabled livestream commerce. Subsequently, PEU is hypothesized to influence PUS, and both PEU and PUS are expected to drive Intention to use (ITU) and Purchase behavior (PBE) through AI-enabled livestream commerce. Based on these theoretical relationships, a total of twelve hypotheses (H1a–H4b, H5–H8) are proposed and consistently applied throughout the manuscript, including the hypotheses development, empirical analysis, and the research model (Figure 1).

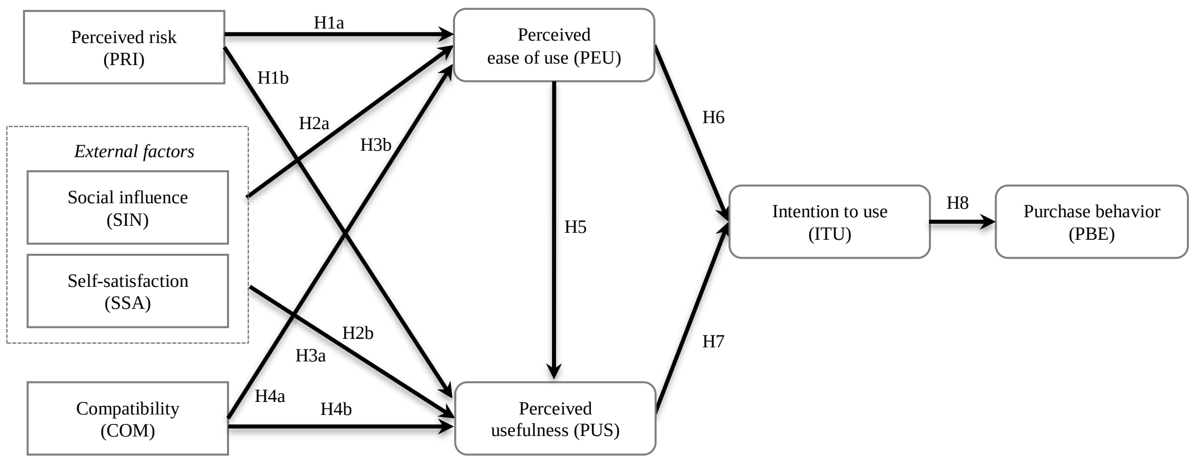

Figure 1. Research model

The Technology Acceptance Model (TAM) posited that perceived ease of use and perceived usefulness are the two core determinants of intention to use technology, which subsequently influence actual usage behavior [32]. The Unified Theory of Acceptance and Use of Technology (UTAUT) extended TAM by incorporating social and psychological factors, thereby offering a more comprehensive explanation of technology acceptance behavior [12, 13]. Perceived ease of use (PEU) refers to users' perception of the degree to which a consumer believes that using live commerce technology will be simple, convenient, and effortless [32]. Perceived usefulness (PUS) refers to users' perception of the extent to which consumers feel that the technology enhances efficiency and provides convenience in their shopping process [32]. Although trust is widely recognized as a critical factor in AI-mediated and online commerce environments, this study does not explicitly model trust as an independent construct [11, 17]. Instead, trust-related perceptions are captured indirectly through perceived risk and perceived usefulness, which have been extensively employed as proxies for trust in technology acceptance and e-commerce research [41]. This approach allows the research model to remain parsimonious while still reflecting key trust-related mechanisms underlying consumer decision-making in AI-enabled livestream commerce.

- *Perceived risk (PRI)* represents consumers' perceived uncertainty and potential adverse consequences associated with using AI-enabled livestream commerce [35]. In AI-driven livestream environments, such risks are amplified by the lack of human presence and concerns regarding algorithmic transparency, system reliability, and data security [17]. Prior studies indicate that perceived risk negatively influences perceived ease of use and perceived usefulness, thereby reducing consumers' intention to use the technology [41]. Hence, concerning perceived risk, hypotheses H1a and H1b are formulated:

H1a: Perceived risk has a negative effect on perceived ease of use.

H1b: Perceived risk has a negative effect on perceived usefulness.

Social Influence (SIN) refers to the degree to which individuals perceive that important others influence their decision to adopt new technologies [31]. In AI-enabled livestream commerce, it reflects the role of peer feedback, online reviews, and social interaction in shaping user perceptions and reinforcing adoption behavior [23]. Prior studies indicate that social influence plays a critical role in fostering positive technology perceptions and intention to use, particularly during the early stages of AI streamer adoption. Thus, for social influence, hypotheses H2a and H2b are formulated:

H2a: Social influence has a positive effect on perceived ease of use.

H2b: Social influence has a positive effect on perceived usefulness.

Self-Satisfaction (SSA) captures consumers' intrinsic feelings of enjoyment and fulfillment when interacting with livestream platforms [31]. In the context of AI-enabled livestream commerce, it reflects the experiential value of engaging with new technologies, including a sense of novelty, self-expression, and staying up-to-date with emerging trends when interacting with AI streamers [31]. Hence, concerning self-satisfaction, hypotheses H3a and H3b are formulated:

H3a: Self-satisfaction has a positive effect on perceived ease of use.

H3b: Self-satisfaction has a positive effect on perceived usefulness.

Compatibility (COM) refers to the extent to which AI-enabled livestream commerce aligns with consumers' existing values and expectations [35]. In this context, it further reflects the degree to which the technology is consistent with users' prior experiences, shopping habits, and familiarity with digital platforms [12]. Thus, hypotheses H4a and H4b are formulated:

H4a: Compatibility has a positive effect on perceived ease of use.

H4b: Compatibility has a positive effect on perceived usefulness.

Intention to Use (ITU) reflects the degree to which a consumer is willing to use AI-enabled livestream platforms in the future [31]. According to the TAM, perceived ease of use directly influences perceived usefulness and technology intention to use [32]. When consumers perceive an AI-enabled livestream platform as easy to operate and effective, they are more likely to continue using the platform and make purchase decisions through it [31]. Hence, for AI-enabled livestream commerce, hypotheses H5, H6 and H7 are formulated:

H5: Perceived ease of use has a positive effect on perceived usefulness.

H6: Perceived ease of use has a positive effect on intention to use.

H7: Perceived usefulness has a positive effect on intention to use.

Purchase Behavior (PBE) reflects the extent to which consumers engage in actual purchasing behavior through AI-enabled livestream platforms [12]. Intention to use is regarded as a critical mediating factor that leads to actual purchasing behavior [31, 36]. In the context of AI-enabled livestream commerce, when consumers exhibit a higher intention to use the platform, their likelihood of engaging in purchasing behavior increases accordingly [42]. Thus, hypothesis H8 is formulated:

H8: Intention to use has a positive effect on consumers' purchase behavior.

3- Research Methods

3-1- Measurement Scale and Data Collection

The study's measurement instruments were adapted from reputable sources to guarantee psychometric integrity. The research model evaluates eight key constructs: PRI, SIN, SSA, COM, PEU, PUS, ITU, and PBE. In line with Likert-scale development, each construct is measured using multiple items. Data were collected using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Data were collected through a survey conducted between September and December 2025. The target population was consumers in Vietnam who had previously watched, interacted with, or made purchases through livestream shopping sessions incorporating AI technologies or virtual streamers (AI streamers) on social commerce platforms. All measurement items were adapted from prior studies and are presented in Appendix I to ensure transparency and reproducibility.

Online survey methods were employed using a combination of convenience and snowball sampling techniques. A total of 354 questionnaires were distributed, yielding 248 valid responses. After data screening, incomplete responses and those that did not meet the AI livestream experience criteria were excluded from further analysis. The final sample primarily consisted of young, well-educated respondents living in urban areas. This demographic structure closely reflects the typical user profile of AI-enabled livestream commerce in Vietnam, where adoption is concentrated in major metropolitan areas and supported by high levels of digital literacy. While the sample size may be considered relatively modest, it satisfies the minimum requirements for Partial Least Squares Structural Equation Modeling (PLS-SEM), as it exceeds the recommended threshold based on the "10-times rule" and is consistent with prior studies employing variance-based SEM in similar contexts [43].

Although convenience and snowball sampling may limit the generalizability of the findings, the sample characteristics are consistent with the primary user segment of AI-enabled livestream commerce, which is predominantly young, urban, and digitally literate [7, 38]. Thus, the sample is appropriate for capturing early-stage adoption behavior in emerging AI-driven commerce environments. Similar sampling approaches have been widely adopted in prior studies on digital commerce and technology acceptance, particularly when examining new or rapidly evolving technological contexts [43]. The collected data were coded and analyzed using SmartPLS and SPSS software. The assessment procedure included reliability analysis, convergent and discriminant validity testing, and PLS-SEM to evaluate the structural relationships among the proposed constructs.

3-2- Descriptive Statistics

The gender distribution of the sample is relatively balanced, with 51.6% female, 47.3% male, and 1.1% identifying as other, suggesting no notable gender differences in participation in livestream commerce. In terms of age, the majority of respondents fall within the 20–30 age group (66.9%), representing the core segment of young and digitally active consumers in AI-enabled livestream shopping. Respondents under the age of 20 account for 21.5%, while those aged 31–40 represent 9.6%. Older age groups are less represented, with 1.7% aged 41–50 and only 0.3% above 50, indicating a limited representation of older consumers in the sample. Regarding educational background, most respondents hold a bachelor's degree (89.8%), followed by postgraduate qualifications (8.3%). A smaller proportion of participants have upper secondary education (2%) or college/vocational training (1.4%). In terms of monthly expenditure on AI-enabled livestream shopping platforms (e.g., TikTok, Shopee…), the majority of respondents (62%) spend less than VND 1 million. Approximately 31.2% report spending between VND 1–5 million, while only a small proportion spend between VND 5–10 million (3.7%) or above VND 10 million (3.1%).

4- Research Results

4-1- Measurement Model Assessment

Convergent validity and reliability were assessed to evaluate the adequacy of the measurement model in the context of AI-enabled livestream commerce [6]. The analysis was conducted using SmartPLS, focusing on the relationships among latent constructs related to consumers' technology acceptance and purchasing behavior toward livestream platforms integrated with AI streamers. Table 1 presents the study constructs together with their corresponding measurement indicators, namely outer loadings, Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). Outer loadings should exceed 0.70 to ensure adequate convergent validity, indicating that each measurement item shares a substantial proportion of variance with its underlying construct [44].

Table 1. Assessment of measurement model

Construct and Item	Outer loading	Cronbach's Alpha	CR	AVE
Compatibility				
COM1	0.889			
COM2	0.902	0.877	0.924	0.803
COM3	0.896			
Perceived ease of use				
PEU1	0.922	0.820	0.918	0.848
PEU2	0.919			
Perceived risk				
PRI1	0.828			
PRI2	0.814	0.773	0.955	0.843
PRI3	0.843			
Perceived usefulness				
PUS1	0.944	0.880	0.932	0.775
PUS2	0.946			
Social influence				
SIN1	0.895			
SIN2	0.869	0.858	0.933	0.777
SIN3	0.884			
Self-satisfaction				
SSA1	0.884			
SSA2	0.873	0.840	0.904	0.758
SSA3	0.855			
Intention to use				
ITU1	0.907	0.786	0.903	0.824
ITU2	0.908			
Purchase behavior				
PBE1	0.930	0.831	0.922	0.855
PBE2	0.920			

In this study, all outer loadings range from 0.758 to 0.944, which exceeds the recommended threshold and suggests strong item reliability. These results confirm that the measurement indicators are well aligned with their respective latent constructs and are capable of capturing the intended conceptual meanings within the context of AI-enabled livestream commerce. Consequently, the measurement model demonstrates satisfactory reliability and validity. Besides, all constructs exhibit Cronbach’s Alpha and Composite Reliability values exceeding 0.70, thereby confirming strong internal consistency. In addition, all AVE values are greater than 0.50, indicating that each construct explains a substantial proportion of variance in its indicators and thereby establishing convergent validity of the measurement model (Table 1).

4-2- Structural Model Assessment

A Variance Inflation Factor (VIF) value exceeding 5 indicates potential multicollinearity [43]. All VIF values obtained from the SmartPLS analysis are below the threshold of 5, indicating no multicollinearity issues in the model (Table 5).

These results indicate that the structural model examining consumers’ technology acceptance and purchasing behavior toward livestream platforms integrated with AI streamers does not suffer from multicollinearity. Therefore, the findings confirm that the model demonstrates adequate validity and reliability, providing a sound basis for subsequent hypothesis testing and structural model evaluation. All measurement indicators met the acceptable outer loading threshold, confirming the adequacy of the measurement model. The PLS-SEM approach was adopted due to its flexibility and suitability for analyzing complex models in emerging technology contexts [44]. To evaluate the statistical significance and stability of the estimated parameters without requiring multivariate normality, a bootstrapping procedure was conducted. The results of the measurement model assessment, including reliability, convergent validity, and discriminant validity, demonstrate that the proposed model satisfies the required criteria for structural analysis and hypothesis testing. Detailed results are presented in Tables 2 and 3.

Table 2. **Discriminant validity - HTMT**

	HTMT							
	COM	**PEU**	**PRI**	**PUS**	**SIN**	**SSA**	**ITU**	**PBE**
COM	-							
PEU	0.849	-						
PRI	0.142	0.270	-					
PUS	0.767	0.730	0.310	-				
SIN	0.702	0.618	0.145	0.717	-			
SSA	0.750	0.742	0.306	0.768	0.735	-		
ITU	0.791	0.845	0.266	0.801	0.752	0.806	-	
PBE	0.657	0.666	0.210	0.727	0.734	0.822	0.724	-

Table 3. **Discriminant validity - Fornell Lacker**

	Fornell Lacker							
	COM	**PEU**	**PRI**	**PUS**	**SIN**	**SSA**	**ITU**	**PBE**
COM	**0.896**							
PEU	0.722	**0.921**						
PRI	–0.118	–0.220	**0.828**					
PUS	0.675	0.620	–0.257	**0.945**				
SIN	0.609	0.518	–0.117	0.623	**0.883**			
SSA	0.643	0.616	–0.244	0.661	0.624	**0.896**		
ITU	0.656	0.678	–0.210	0.666	0.618	0.655	**0.908**	
PBE	0.559	0.550	–0.170	0.622	0.621	0.687	0.585	**0.925**

Accordingly, hypotheses with p-values < 0.05 were accepted, while those with p-values > 0.05 were rejected. The structural model analysis demonstrates that both technological and psychological–social factors significantly influence Perceived ease of use (PEU), Perceived usefulness (PUS), and Intention to use (ITU) toward livestream platforms integrated with AI streamers, which in turn affect consumers' actual Purchase behavior (PBE). Specifically, perceived risk exerts a negative effect on both PEU and PUS, reflecting consumers' caution when interacting with AI streamers. In contrast, social influence, self-satisfaction, and compatibility positively contribute to the formation of favorable technology perceptions. Although the effect of PEU on PUS is not statistically significant, PUS remains the primary driver of ITU. Furthermore, ITU serves as a key mediating mechanism that strongly influences PBE in AI-enabled livestream commerce (Table 4 and Figure 2). Overall, the results provide strong empirical support for the proposed research model in the context of AI-enabled livestream commerce.

Table 4. **SEM and hypothesis testing results**

H	Path	Coefficient	SD	t statistics	p-value	VIF	Result
H1a	PRI → PEU	–0.098	0.041	2.413	0.016	1.068	Accepted
H1b	PRI → PUS	–0.111	0.046	2.433	0.015	1.090	Accepted
H2a	SIN → PEU	0.039	0.067	0.576	0.564	1.864	Rejected
H2b	SIN → PUS	0.227	0.068	3.331	0.001	1.867	Accepted
H3a	SSA → PEU	0.216	0.069	3.119	0.002	2.098	Accepted
H3b	SSA → PUS	0.229	0.081	2.841	0.005	2.206	Accepted
H4a	COM → PEU	0.548	0.079	6.924	0.000	1.941	Accepted
H4b	COM → PUS	0.277	0.086	3.203	0.001	2.640	Accepted
H5	PEU → PUS	0.137	0.080	1.714	0.087	2.327	Rejected
H6	PEU → ITU	0.431	0.077	5.565	0.000	1.626	Accepted
H7	PUS → ITU	0.398	0.079	5.020	0.000	1.626	Accepted
H8	ITU → PBE	0.585	0.047	12.534	0.000	1.000	Accepted

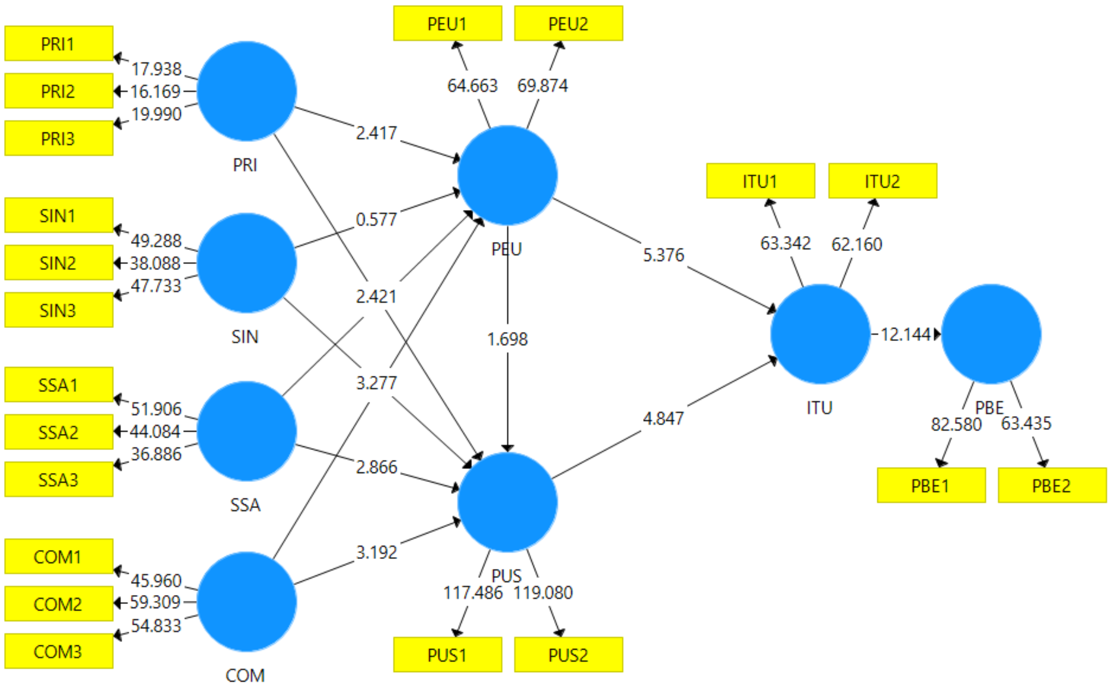

Figure 2. **PLS-SEM Results**

To assess the extent to which variance in each endogenous construct is explained by its predictors, the coefficient of determination (R^2) was examined [45]. The R^2 results derived from the SmartPLS analysis are summarized in Table 5. For PBE, the adjusted R^2 value is 0.340, indicating that ITU explains 34% of the variance in consumers' purchasing behavior in AI-enabled livestream commerce. Regarding ITU, the construct is influenced by PEU and PUS, yielding an adjusted R^2 value of 0.554. Although several hypothesized paths were not statistically significant, perceived usefulness remains the strongest predictor of intention to use, explaining a substantial proportion of variance (adjusted R^2 = 0.554). For PEU, the construct is influenced by PRI, SIN, SSA, and COM, yielding an adjusted R^2 value of 0.563, indicating that these factors jointly explain 56.3% of the variance. In addition, Stone–Geisser's Q^2 values were calculated to assess the model's out-of-sample predictive relevance, as reported in Table 5. All Q^2 values exceed 0.25, indicating at least moderate predictive accuracy. Among the endogenous constructs, perceived ease of use exhibits the highest Q^2 value, followed by intention to use, and finally purchase behavior, confirming the model's strong predictive capability in explaining consumers' adoption and purchasing behavior toward AI streamers.

Table 5. **R^2 and Q^2**

	R^2	Adjusted R^2	Q^2
ITU	0.558	0.554	0.445
PBE	0.343	0.340	0.287
PEU	0.570	0.563	0.470
PUS	0.593	0.585	0.514

4-3- Discussion

This study provides empirical evidence on consumer purchase behavior in AI-enabled livestream commerce, an emerging form of AI-driven digital retail in Vietnam. The findings highlight that consumer responses in this context are shaped by a combination of technological perceptions, psychological mechanisms, and social influences. This result is consistent with prior research on digital commerce, which emphasizes that consumer behavior in online environments is not solely determined by system functionality but also by broader cognitive and social processes [11, 12].

The significant effects of perceived usefulness and perceived ease of use reaffirm the central role of technology acceptance mechanisms in AI-mediated commerce. However, unlike traditional e-commerce settings, these perceptions in AI-enabled livestream environments extend beyond system usability to include consumers' ability to interpret and interact with AI-generated content. This finding aligns with prior studies suggesting that utilitarian value remains a dominant driver of adoption, particularly in emerging markets where consumers tend to evaluate new technologies cautiously [10, 11, 46].

Compatibility emerges as the most influential factor affecting perceived ease of use, indicating that consumers are more likely to accept AI-enabled livestream platforms when these systems align with their existing shopping habits and prior digital experiences. This result supports earlier findings on innovation diffusion and technology adoption, which emphasize the importance of consistency between new technologies and users' existing routines [36]. In the context of AI streamers, compatibility reduces cognitive effort and uncertainty, thereby facilitating smoother interaction and enhancing user acceptance.

The negative influence of perceived risk on both perceived ease of use and perceived usefulness underscores the importance of uncertainty reduction in AI-mediated commerce. This finding is consistent with prior studies in e-commerce and social commerce, which highlight perceived risk as a critical barrier to adoption [10, 20, 27]. In AI-enabled livestream settings, this effect becomes more pronounced due to the absence of human presence and emotional authenticity. Consumers may question the reliability, transparency, and trustworthiness of AI streamers, which in turn affects their overall evaluation of the platform.

The role of social influence presents a more nuanced pattern. While it significantly enhances perceived usefulness, its effect on perceived ease of use is not supported. This result partially aligns with UTAUT, which suggests that social influence plays a stronger role in shaping perceived value rather than usability perceptions [12, 13]. In AI-enabled livestream commerce, social cues such as peer recommendations, online comments, and community engagement may legitimize the use of AI streamers and reinforce perceived benefits, but they may not directly reduce the effort required to use the system.

Self-satisfaction also contributes positively to both perceived ease of use and perceived usefulness, highlighting the importance of intrinsic motivation in AI-driven environments. This finding is consistent with prior research indicating that enjoyment, novelty, and self-expression play significant roles in shaping user engagement with emerging technologies [31]. In the context of AI streamers, interacting with advanced technology may provide users with a sense of novelty and technological sophistication, thereby enhancing their overall evaluation of the platform.

Interestingly, the effect of perceived ease of use on perceived usefulness was not statistically supported, suggesting that consumers evaluate the usefulness of AI-enabled livestream commerce independently of usability perceptions. This finding may reflect the unique characteristics of AI-enabled livestream environments, where consumers place greater emphasis on the functional value and benefits provided by AI streamers than on the ease of interacting with the platform. Nevertheless, perceived ease of use and perceived usefulness both significantly influenced intention to use, supporting the continued relevance of TAM and UTAUT in explaining consumer behavior in AI-enabled environments. Notably, intention to use acts as a key mediating mechanism that translates cognitive evaluations into actual purchasing behavior, consistent with prior studies on technology adoption and digital commerce [12, 13, 31].

Overall, the findings suggest that AI-enabled livestream commerce represents not merely a technological innovation but a transformation in consumer–platform interaction. While AI streamers offer advantages in terms of scalability, consistency, and personalization, their effectiveness ultimately depends on how well they address users' concerns related to trust, usability, and social validation. By integrating technological and social–psychological perspectives, this study provides a more comprehensive understanding of how AI reshapes consumer behavior in emerging digital commerce ecosystems. The inclusion of measurement items in Appendix I further enhances the transparency of the study.

5- Conclusion

5-1- Research Summary

This study examines consumer purchase behavior in AI-enabled livestream commerce by integrating technological and social–psychological factors within an extended TAM–UTAUT framework. The findings indicate that perceived risk, social influence, self-satisfaction, and compatibility exert differentiated effects on perceived ease of use and perceived usefulness. Among these factors, compatibility emerges as the strongest determinant of perceived ease of use, highlighting the importance of aligning AI-enabled livestream systems with users' existing shopping habits and preferences. In contrast, perceived risk, social influence, and self-satisfaction demonstrate varying levels of influence depending on the specific relationships examined. Furthermore, perceived ease of use and perceived usefulness significantly shape intention to use, which in turn strongly drives purchase behavior in AI-enabled livestream commerce.

The results underscore the central role of perceived usefulness in encouraging consumer adoption, suggesting that users are more likely to engage with AI streamers when they perceive clear functional benefits, efficiency, and value in the shopping process. Overall, the findings highlight that enhancing compatibility and self-satisfaction, while effectively managing perceived risk, is essential for fostering consumer acceptance and sustained engagement. This study contributes to the literature by extending the applicability of the TAM–UTAUT framework to AI-mediated livestream environments and provides practical insights for platform operators and businesses in designing and implementing AI-driven livestream strategies. By emphasizing the interplay between technological efficiency and user perceptions, the study offers a more nuanced understanding of how AI streamers influence consumer behavior in emerging digital commerce contexts.

5-2- Theoretical Implications

This study advances the literature on AI-enabled livestream commerce by extending the Technology Acceptance Model (TAM) and UTAUT to a context where AI streamers function as primary interaction agents [12, 13, 31]. As live commerce continues to evolve into a distinct retail channel that reshapes traditional consumer–seller interactions [47], integrating AI streamers represents a logical progression in this transformation. While prior research has predominantly examined purchase intentions in traditional e-commerce or human-led livestream environments, limited attention has been paid to how consumers cognitively and emotionally evaluate AI-mediated livestream shopping [7]. This study addresses that gap by integrating technological, psychological, and social factors within a unified acceptance framework [13].

The findings confirm that perceived ease of use and perceived usefulness remain central determinants of intention to use, supporting the robustness of TAM in AI-driven environments [5, 32]. However, in the AI-streamer context, these constructs extend beyond system usability to include consumers' ability to understand, trust, and interact smoothly with AI-generated content [11]. This highlights the need to reinterpret core TAM variables when human–AI interaction replaces human streamers [16]. Moreover, the results underscore the critical role of perceived risk as a key inhibitor of technology acceptance in AI livestream commerce [41]. Concerns related to data security, algorithmic transparency, and the absence of human judgment negatively influence consumers' evaluations of both ease of use and usefulness, emphasizing the importance of incorporating technology-related uncertainty into acceptance models for AI-mediated commerce [17]. In addition, the significant effects of social influence, self-satisfaction, and compatibility demonstrate that AI livestream commerce operates as a social–emotional consumption environment, rather than a purely functional system [48]. These findings extend UTAUT by showing that intrinsic motivation and social cues remain influential even when interaction occurs with virtual rather than human streamers [31]. Finally, the study provides empirical support for the intention–behavior linkage, confirming that intention to use strongly predicts actual purchase behavior in AI livestream settings [12, 13, 31]. Overall, this research enriches technology acceptance theory by contextualizing TAM and UTAUT within AI-driven livestream commerce, offering a more nuanced understanding of consumer adoption and purchasing behavior in AI-streamer–mediated environments [5].

5-3- Practical Implications

The findings show that consumers' purchase intentions in AI-enabled livestream commerce are driven by psychological and perceptual factors - perceived risk, social influence, self-satisfaction, and compatibility through perceived ease of use, perceived usefulness, and intention to use. These results offer several managerial implications.

First, perceived risk significantly inhibits positive technology evaluations in AI-streamer contexts. To reduce uncertainty, firms should enhance transparency regarding product information, data privacy, payment security, and return policies. Hybrid livestream formats that combine AI streamers with human hosts may further strengthen trust and emotional reassurance. Second, social influence positively shapes consumers' perceptions of AI livestream technologies. Leveraging influencers, KOLs, visible viewer metrics, and user-generated reviews can reinforce social validation and accelerate adoption, particularly during early implementation stages. Third, self-satisfaction highlights the importance of emotional engagement. Designing entertaining and personalized livestream experiences such as interactive responses, gamified elements, and intelligent product recommendations can enhance enjoyment and reduce psychological resistance. Finally, compatibility emerges as the strongest determinant of perceived ease of use. AI livestream systems should align closely with consumers' existing shopping habits through intuitive interfaces and personalized content. Overall, effective AI livestream strategies require balancing technological efficiency with emotional connection and social trust to foster sustained consumer adoption and purchase intention.

5-4- Limitations and Future Works

Despite its contributions, this study is subject to several limitations that provide avenues for future research. First, the use of a cross-sectional research design restricts the ability to establish causal relationships and does not capture potential changes in consumers' perceptions and purchasing behavior over time. Future studies could adopt longitudinal or experimental approaches to better examine the dynamic nature of consumer behavior in AI-enabled livestream commerce. Second, the data were collected from a single country, which may limit the generalizability of the findings. Future research could extend this study to different geographical contexts or conduct cross-cultural comparisons to enhance external validity. Third, the proposed model focuses primarily on selected psychological and perceptual factors. Future studies may consider incorporating additional variables, such as trust in AI streamers, perceived anthropomorphism, or platform-specific features, to provide a more comprehensive understanding of consumer behavior in AI-driven environments. Finally, the reliance on self-reported data may introduce potential biases, including common method bias and social desirability effects. Future research is encouraged to integrate objective behavioral or transactional data to improve the robustness of the findings.

6- Declarations

6-1- Author Contributions

Conceptualization, T.D.N. and H.D.D.L.; methodology, T.D.N. and H.D.D.L.; software, H.D.D.L.; validation, T.D.N.; formal analysis, H.D.D.L.; investigation, T.D.N. and H.D.D.L.; resources, T.D.N. and H.D.D.L.; data curation, H.D.D.L.; writing—original draft preparation, T.D.N. and H.D.D.L.; writing—review and editing, T.D.N.; visualization, T.D.N. and H.D.D.L; supervision, T.D.N. All authors have read and agreed to the published version of the manuscript.

6-2- Data Availability Statement

The data presented in this study are available from the corresponding author upon reasonable request.

6-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6-4- Institutional Review Board Statement

Ethical approval was not required under applicable national regulations for anonymous survey-based research involving adult participants.

6-5- Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

6-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

7- References

[1] Cunha, M. N., & Krupskyi, O. P. (2025). Transforming Online Retail: The Impact of Augmented and Virtual Reality on Consumer Engagement and Experience in E-Commerce. Current Progress in Arts and Social Studies Research, 10, 95–112. doi:10.9734/bpi/cpassr/v10/4425.

[2] Wang, L., Yeap, J. A. L., Liu, J., & Li, Z. (2026). From Avatars to Algorithms: Virtual Streamers and AI-Enabled Consumer Behavior in Live Streaming Commerce—A Systematic Review. Journal of Theoretical and Applied Electronic Commerce Research, 21(2), 57. doi:10.3390/jtaer21020057.

[3] Liu, M., Chen, X., Yang, B., & Gao, Y. (2025). The role of social presence in impulsive buying during live streaming E-commerce: exploring the mechanisms of customer inspiration and positive emotion. BMC psychology, 13(1), 1414. doi:10.1186/s40359-025-03743-4.

[4] Yuan, D. H., Deng, R., & Lin, Z. (2026). When the thrill lingers: how post-purchase flow consciousness shapes live-stream shopping engagement. European Journal of Marketing, 1-21. doi:10.1108/EJM-09-2024-0783/1336798.

[5] Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., Jain, V., Karjaluoto, H., Kefi, H., Krishen, A. S., Kumar, V., Rahman, M. M., Raman, R., Rauschnabel, P. A., Rowley, J., Salo, J., Tran, G. A., & Wang, Y. (2021). Setting the future of digital and social media marketing research: Perspectives and research propositions. International Journal of Information Management, 59. doi:10.1016/j.ijinfomgt.2020.102168.

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

[7] 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. doi:10.1016/j.jbusres.2018.08.032.

[8] Wang, Z. (2025). The influence of AI on consumer behavior: Shaping choices and preferences in the digital marketplace. Systems and Soft Computing, 200397. doi:10.1016/j.sasc.2025.200397.

[9] Liang, T. P., Ho, Y. T., Li, Y. W., & Turban, E. (2011). What drives social commerce: The role of social support and relationship quality. International Journal of Electronic Commerce, 16(2), 69–90. doi:10.2753/JEC1086-4415160204.

[10] Hajli, N., Sims, J., Zadeh, A. H., & Richard, M. O. (2017). A social commerce investigation of the role of trust in a social networking site on purchase intentions. Journal of Business Research, 71, 133–141. doi:10.1016/j.jbusres.2016.10.004.

[11] Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and tam in online shopping: An integrated model. MIS Quarterly, 27(1), 51–90. doi:10.2307/30036519.

[12] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly: Management Information Systems, 27(3), 425–478. doi:10.2307/30036540.

[13] Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1), 157–178. doi:10.2307/41410412.

[14] Ni, S., & Ueichi, H. (2024). Factors influencing behavioral intentions in livestream shopping: A cross-cultural study. Journal of Retailing and Consumer Services, 76, 103596. doi:10.1016/j.jretconser.2023.103596.

[15] Sun, L., & Tang, Y. (2024). Avatar effect of AI-enabled virtual streamers on consumer purchase intention in e-commerce livestreaming. Journal of Consumer Behaviour, 23(6), 2999–3010. doi:10.1002/cb.2389.

[16] Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48(1), 24–42. doi:10.1007/s11747-019-00696-0.

[17] 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. doi:10.1080/10864415.2003.11044275.

[18] 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. doi:10.1016/j.elerap.2019.100886.

[19] Verhoef, P. C., Kannan, P. K., & Inman, J. J. (2015). From Multi-Channel Retailing to Omni-Channel Retailing. Introduction to the Special Issue on Multi-Channel Retailing. Journal of Retailing, 91(2), 174–181. doi:10.1016/j.jretai.2015.02.005.

[20] Yun, J., Lee, D., Cottingham, M., & Hyun, H. (2023). New generation commerce: The rise of live commerce (L-commerce). Journal of Retailing and Consumer Services, 74. doi:10.1016/j.jretconser.2023.103394.

[21] Seo, H., & Kim, S. Y. (2022). The Effect of Non-face-to-face Collaboration System Quality on Business Performance. 2022 IEEE/ACIS 7th International Conference on Big Data, Cloud Computing, and Data Science (BCD), 70–75. doi:10.1109/BCD54882.2022.9900701.

[22] Ruangkanjanases, A., & Hariguna, T. (2025). Investigating the Correlation between Bitcoin Trading Volume and Technical Indicators Using Data Mining Techniques. HighTech and Innovation Journal, 6(4), 1390–1400. doi:10.28991/HIJ-2025-06-04-015.

[23] Moloi, T., & Marwala, T. (2020). Artificial Intelligence in Economics and Finance Theories. Springer Nature, Cham, Switzerland. doi:10.1007/978-3-030-42962-1.

[24] Russell, S. J. (2010). Artificial intelligence a modern approach. Pearson Education, London, United Kingdom.

[25] Bickley, S. J., Chan, H. F., & Torgler, B. (2022). Artificial intelligence in the field of economics. Scientometrics, 127(4), 2055-2084. doi:10.1007/s11192-022-04294-w.

[26] Choi, P. M. S., & Huang, S. H. Fintech with Artificial Intelligence, Big Data, and Blockchain. Springer Nature, Cham, Switzerland. doi:10.1007/978-981-33-6137-9.

[27] Voskoglou, M. G., & Salem, A. B. M. (2020). Benefits and limitations of the artificial with respect to the traditional learning of mathematics. Mathematics, 8(4), 611. doi:10.3390/math8040611.

[28] Neumann, O., Guirguis, K., & Steiner, R. (2024). Exploring artificial intelligence adoption in public organizations: a comparative case study. Public Management Review, 26(1), 114–141. doi:10.1080/14719037.2022.2048685.

[29] G. Harkut, D. (Ed.). (2019). Artificial Intelligence - Scope and Limitations. IntechOpen, London, United Kingdom. doi:10.5772/intechopen.77611.

[30] Madanchian, M., & Taherdoost, H. (2025). Barriers and Enablers of AI Adoption in Human Resource Management: A Critical Analysis of Organizational and Technological Factors. Information (Switzerland), 16(1), 51. doi:10.3390/info16010051.

[31] Venkatesh, V. (2022). Adoption and use of AI tools: a research agenda grounded in UTAUT. Annals of Operations Research, 308(1–2), 641–652. doi:10.1007/s10479-020-03918-9.

[32] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–339. doi:10.2307/249008.

[33] Venkatesh, V., & Davis, F. D. (2000). Theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. Management Science, 46(2), 186–204. doi:10.1287/mnsc.46.2.186.11926.

[34] Silva, P. (2015). Davis' technology acceptance model (TAM) (1989). Information seeking behavior and technology adoption: Theories and trends, 205-219, IGI Global Scientific Publishing, Hershey, United States. doi:10.4018/978-1-4666-8156-9.ch013.

[35] Phamthi, V. A., Nagy, Á., & Ngo, T. M. (2024). The influence of perceived risk on purchase intention in e-commerce Systematic review and research agenda. International Journal of Consumer Studies, 48(4), e13067. doi:10.1111/ijcs.13067.

[36] Turki, H. (2025). AI-Powered Personalization in E-Commerce: Governance, Consumer Behavior, and Explanatory Insights from Big Data Analytics. Technology in Society, 103033. doi:10.1016/j.techsoc.2025.103033.

[37] Li, L., Feng, Y., & Zhao, A. (2024). An interaction–immersion model in live streaming commerce: the moderating role of streamer attractiveness. Journal of Marketing Analytics, 12(3), 701-716. doi:10.1057/s41270-023-00225-7.

[38] Huang, M. H., & Rust, R. T. (2018). Artificial Intelligence in Service. Journal of Service Research, 21(2), 155–172. doi:10.1177/1094670517752459.

[39] Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. Information Systems Research, 6(2), 144–176. doi:10.1287/isre.6.2.144.

[40] Maidiana, K., & Hidayat, Z. (2021). Distributing Goods and Information Flow: Factors Influencing Online Purchasing Behavior of Indonesian Consumers. Journal of Distribution Science, 19(7), 5–17. doi:10.15722/jds.19.7.202107.5.

[41] Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. International Journal of Human Computer Studies, 59(4), 451–474. doi:10.1016/S1071-5819(03)00111-3.

[42] Zhang, Q., Wang, Y., & Ariffin, S. K. (2024). Consumers purchase intention in live-streaming e-commerce: A consumption value perspective and the role of streamer popularity. Plos one, 19(2), e0296339. doi:10.1371/journal.pone.0296339.

[43] Sarstedt, M., Ringle, C.M., Hair, J.F. (2022). Partial Least Squares Structural Equation Modeling, Handbook of Market Research. Springer, Cham, Switzerland. doi:10.1007/978-3-319-57413-4_15.

[44] Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. Research Methods in Applied Linguistics, 1(3), 100027. doi:10.1016/j.rmal.2022.100027.

[45] Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. European Journal of Marketing, 53(11), 2322–2347. doi:10.1108/EJM-02-2019-0189.

[46] Zhou, T., Lu, Y., & Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. Computers in Human Behavior, 26(4), 760–767. doi:10.1016/j.chb.2010.01.013.

[47] Zhang, K. Z. K., & Benyoucef, M. (2016). Consumer behavior in social commerce: A literature review. Decision Support Systems, 86, 95–108. doi:10.1016/j.dss.2016.04.001.

[48] Bagozzi, R. P. (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift. Journal of the Association for Information Systems, 8(4), 244–254. doi:10.17705/1jais.00122.

Appendix I: Measurement Items

Construct		Item	Reference
Compatibility	COM1	Using VLS is compatible with my existing shopping habits	Liu et al. [35]
	COM2	VLS aligns with my personal shopping style	
	COM3	Using VLS fits well with the way I like to shop	
Perceived ease of use	PEU1	Learning to shop via VLS is easy for me	Davis [32]
	PEU2	I find VLS convenient and easy to use	
Perceived risk	PRI1	I am concerned that VLS might not be able to provide products that meet my expectations	Liu et al. [35]
	PRI2	I feel insecure about sharing my personal information on VLS platforms	
	PRI3	I am concerned that others might judge me for shopping via VLS	
Perceived usefulness	PUS1	Using VLS enhances my shopping efficiency	Davis [32]
	PUS2	Using VLS improves my shopping effectiveness	
Social influence	SIN1	People who are close to me encourage the use of VLS	Venkatesh [31]
	SIN2	I tend to adopt VLS based on the influence of those around me	
	SIN3	People who are important to me assist me in using VLS	
Self-satisfaction	SSA1	Using VLS keeps me up-to-date with the latest trends	Venkatesh [31]
	SSA2	I feel a sense of satisfaction when using VLS	
	SSA3	I feel that I have successfully kept pace with VLS technology	
Intention to use	ITU1	I am interested in using VLS platforms	Venkatesh [31]
	ITU2	I intend to use VLS for my shopping activities	
Purchase behavior	PBE1	I am inclined to purchase products while watching VLS livestream sessions	Zhang & Benyoucef [47]
	PBE2	I am likely to make purchases based on the recommendations provided by VLS	

VLS: Virtual Live Streamers.