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BUILDING TRUST THROUGH AI: HOW INTERACTION FEATURES DRIVE IMPULSE BUYING IN LIVESTREAM COMMERCE

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ABSTRACT

This study examines how AI-driven interaction features shape consumer trust and impulse buying behavior in livestream commerce within the Stimulus-Organism-Response (S-O-R) framework. AI-driven interaction is conceptualized through three dimensions: hedonic interaction, personalization, and adaptive support. Data were collected from 480 consumers with prior livestream shopping experience in Vietnam and analyzed using Structural Equation Modeling (SEM). The results show that all three AI-driven interaction features significantly enhance consumer trust and directly influence impulse buying behavior. Adaptive support has the strongest effect on trust, whereas personalization exerts the strongest direct effect on impulse buying. Trust also has a significant positive effect on impulse buying behavior. These findings demonstrate that different AI-driven interaction features play distinct roles in shaping consumers' cognitive evaluations and behavioral responses in livestream commerce. The study extends the S-O-R framework to AI-enabled livestream environments and highlights the importance of designing AI interactions that combine responsiveness, personalization, and engaging experiences to strengthen consumer trust and stimulate purchasing behavior.

Keywords: AI-driven interaction, livestream commerce, trust, impulse buying behavior, personalization.

1. INTRODUCTION

The rapid convergence of artificial intelligence (AI) and livestream commerce is fundamentally reshaping consumer behavior in digital environments. Livestream commerce integrates real-time interaction with transactional functionality, enabling dynamic communication between sellers and consumers and thereby influencing purchasing decisions [1], [2].

AI technologies further enhance this environment by enabling personalized recommendations, adaptive support, and intelligent interaction features that improve system responsiveness, service quality, and perceived relevance [3]-[5]. These capabilities are expected to reduce uncertainty and facilitate consumer decision-making in increasingly complex digital contexts.

However, existing research has primarily focused on general technological characteristics of online commerce, with limited attention to the distinct roles of specific AI-driven interaction features. In particular, the mechanisms through which these AI capabilities influence consumer behavior remain insufficiently understood.

Trust has been widely recognized as a critical determinant of consumer behavior in online commerce because it mitigates perceived risk and facilitates decision-making under uncertainty [5], [6]. In livestream commerce, where consumers rely heavily on mediated communication and real-time interactions, trust becomes even more important. Nevertheless, limited empirical attention has been devoted to how trust, as a cognitive state, is shaped by AI-driven interaction features and subsequently associated with impulse buying behavior.

Drawing upon the Stimulus-Organism-Response (S-O-R) framework [7], [8], this study conceptualizes AI-driven interaction features-namely hedonic interaction, personalization, and adaptive support as technological stimuli that influence consumers' trust as an organismic cognitive state, which subsequently drives impulse buying behavior.

This study contributes to the literature in three ways. First, it extends the S-O-R framework to AI-enabled livestream commerce by conceptualizing AI-driven interaction as a multidimensional construct. Second, it clarifies how AI-driven interaction features contribute to consumer trust and how trust, in turn, influences impulse buying behavior. Third, it provides practical implications for leveraging AI capabilities to strengthen consumer engagement and purchasing behavior in real-time digital commerce environments.

2. LITERATURE REVIEW

2.1. Theoretical foundation of the S-O-R framework

The Stimulus-Organism-Response (S-O-R) framework provides a well-established theoretical foundation for explaining consumer behavior in technology-mediated environments [7], [8]. According to this framework, external environmental stimuli influence individuals' internal cognitive and psychological states, which subsequently shape behavioral responses. In digital commerce research, the S-O-R framework has been widely applied to explain how technological affordances, interface characteristics, and interaction mechanisms influence consumers' perceptions, evaluations, and purchasing behavior [9].

Livestream commerce represents a particularly appropriate context for applying the S-O-R framework because it integrates real-time interaction, continuous information exposure, social communication, and transactional functionality within a highly dynamic digital ecosystem [1], [2]. Compared with conventional online shopping, livestream commerce creates a more immersive and interactive decision-making environment in which consumers are continuously exposed to persuasive stimuli and immediate purchasing opportunities. Such conditions accelerate decision-making while simultaneously increasing consumers' reliance on platform-related cues during purchase evaluation.

Despite these interactive advantages, livestream commerce also introduces substantial uncertainty and information asymmetry. Consumers frequently rely on mediated communication rather than direct product inspection, while time pressure and continuous interaction reduce opportunities for extensive cognitive processing [1], [2]. Consequently, consumers increasingly depend on technological and relational cues to evaluate credibility, reduce uncertainty, and facilitate purchasing decisions.

Within this context, artificial intelligence (AI) has emerged as a transformative technological mechanism capable of fundamentally reshaping consumer interaction in livestream commerce. Unlike conventional static systems, AI-enabled technologies dynamically personalize content, provide adaptive assistance, and facilitate intelligent interaction in real time [10], [4]. These capabilities not only improve operational efficiency and interaction quality but also influence consumers' perceptions of responsiveness, relevance, competence, and credibility throughout the livestream shopping experience.

Accordingly, this study conceptualizes AI-driven interaction features as technological stimuli, trust as the organismic cognitive state, and impulse buying behavior as the behavioral response within the S-O-R framework. Specifically, hedonic interaction, personalization, and adaptive support represent three complementary dimensions of AI-driven interaction that shape consumers' cognitive evaluations and behavioral responses in livestream commerce.

2.1.1. AI-driven interaction features

AI-driven interaction features represent intelligent technological capabilities that enhance interaction quality, user engagement, and decision support in digital commerce environments. Prior research has emphasized the transformative role of artificial intelligence in marketing and service systems, particularly in improving responsiveness, personalization, customer experience, and service effectiveness [3]-[5].

In livestream commerce, AI-driven interaction features can be conceptualized through three major dimensions: hedonic interaction, personalization, and adaptive support.

Hedonic interaction refers to the extent to which AI-enabled systems create enjoyable, entertaining, and immersive experiences during livestream sessions. Such interactions strengthen experiential engagement and increase consumers' involvement in the shopping process [11], [12]. In highly interactive digital environments, pleasurable and immersive experiences encourage users to remain engaged for longer periods, thereby increasing the likelihood of spontaneous purchasing behavior.

Personalization reflects the capability of AI systems to tailor recommendations, content, and interaction experiences according to individual consumers' preferences and behavioral patterns. Personalized recommendations reduce information search costs and improve perceived relevance, thereby enhancing consumers' evaluation efficiency and decision convenience [5], [13], [14]. By providing individualized interaction experiences, AI systems create stronger perceptions of relevance and interaction quality.

Adaptive support captures the capability of AI systems to provide timely assistance, responsive communication, and dynamic problem-solving during livestream interactions. Such responsiveness signals system competence and reliability, which are particularly important in uncertain online environments [4], [15]. Consumers are more likely to develop favorable evaluations toward livestream platforms when AI systems effectively address their concerns and provide immediate support during purchasing processes.

Collectively, these AI-driven interaction features transform livestream commerce into a more intelligent, interactive, and consumer-centered environment. However, the effectiveness of these technological capabilities depends largely on how consumers cognitively evaluate AI-enabled interactions, particularly in terms of trust formation.

2.1.2. Trust in AI-enabled livestream commerce

Within the Stimulus-Organism-Response (S-O-R) framework, the organism represents the internal cognitive and psychological processes through which external stimuli are interpreted and evaluated [7], [8]. In digital commerce environments, trust has consistently been recognized as one of the most critical determinants of consumer behavior [5], [6], [16].

Trust refers to consumers' belief that a platform, seller, or technological system is reliable, competent, and capable of acting in their best interests [5]. In livestream commerce, trust becomes particularly important because consumers rely heavily on mediated information and real-time interaction rather than direct physical product evaluation. As a result, trust functions as a cognitive mechanism that reduces perceived risk, enhances confidence, and facilitates decision-making under uncertainty [16].

The role of trust becomes even more critical in AI-enabled environments. Although AI systems improve responsiveness, personalization, and interaction quality, consumers may still experience concerns regarding recommendation accuracy, information credibility, and system transparency. Consequently, before engaging in purchasing behavior, consumers must first evaluate whether AI-driven interactions are reliable and trustworthy.

Prior research suggests that intelligent interaction systems strengthen trust by enhancing perceived competence, responsiveness, and relevance [4], [15]. In livestream commerce, AI-driven interaction features may foster trust by providing smoother communication, more relevant recommendations, and more responsive support experiences. As consumers perceive these interactions to be useful, intelligent, and reliable, their confidence in the livestream platform and purchasing environment increases accordingly.

Accordingly, trust can be conceptualized as the central organismic mechanism through which AI-driven interaction features influence consumer behavior in livestream commerce environments.

2.1.3. Impulse buying behavior

Impulse buying behavior refers to spontaneous and unplanned purchasing decisions that occur with limited cognitive deliberation [17], [18]. Such behavior is commonly stimulated by environmental cues, situational triggers, and persuasive interaction processes that encourage rapid decision-making [9].

Livestream commerce creates highly favorable conditions for impulse buying because it combines real-time interaction, continuous engagement, social influence, time pressure, and immediate purchasing opportunities within a highly dynamic environment [1], [2], [19]-[21]. Features such as time-limited promotions, interactive communication, and immersive livestream experiences can accelerate consumers' decision-making processes and intensify their responsiveness to immediate purchasing opportunities [20], [21].

Although prior studies frequently associate impulse buying with emotional arousal and hedonic motivation, cognitive mechanisms also play a crucial role in facilitating spontaneous purchasing decisions. In livestream commerce, consumers are often required to make rapid decisions under conditions of uncertainty and incomplete information. Under such circumstances, trust reduces perceived risk and lowers cognitive resistance, thereby enabling consumers to make quicker and less deliberative purchasing decisions [17], [18].

Recent studies further emphasize that trust is a critical determinant of consumer behavior in livestream commerce because it strengthens confidence in both the platform and the information communicated during livestream sessions [1]. Therefore, trust can be understood as a facilitating cognitive mechanism that enables consumers to transition more efficiently from evaluation to purchasing behavior in real-time digital environments.

2.1.4. Hypothesis development

Impulse buying behavior refers to a spontaneous and immediate purchasing response characterized by a strong urge to buy with relatively limited prior deliberation [17], [18]. In digital commerce environments, such behavior can be stimulated by technological, atmospheric, and situational cues that increase consumers' engagement, perceived relevance, and responsiveness to purchase opportunities [9], [17]-[20]. Livestream commerce provides a particularly conducive setting for impulse buying because consumers are exposed to real-time interaction, rapidly changing product information, and immediate opportunities to make purchase decisions.

In addition to their effects on trust, AI-driven interaction features may directly influence impulse buying behavior by shaping consumers' immediate shopping experiences. Hedonic interaction can increase enjoyment, engagement, and immersion during livestream shopping, thereby strengthening consumers' responsiveness to spontaneous purchase opportunities. Prior research indicates that enjoyable and interactive shopping environments can stimulate impulse buying by increasing consumers' involvement and reducing deliberative resistance [9], [17], [18]. In AI-enabled livestream commerce, interactive and entertaining AI-supported experiences may therefore encourage consumers to respond more spontaneously to products presented during a livestream. Accordingly, the following hypothesis is proposed:

H3a: Hedonic interaction positively influences impulse buying behavior in livestream commerce.

Personalization may also directly contribute to impulse buying behavior by increasing the perceived relevance of products, recommendations, and promotional information. AI-enabled personalization allows shopping content to be aligned more closely with consumers' interests and preferences, making purchase opportunities more salient and reducing the cognitive effort required to identify relevant products [3], [13], [14]. In livestream environments, where purchasing decisions are often made rapidly, personalized recommendations may increase consumers' immediate attraction to presented products and strengthen spontaneous purchase responses. Therefore:

H3b: Personalization positively influences impulse buying behavior in livestream commerce.

Adaptive support represents another AI-driven interaction feature that may directly influence impulse buying behavior. By providing timely responses, relevant information, and context-sensitive assistance, adaptive AI systems can enhance interaction responsiveness and reduce consumers' uncertainty during technology-mediated service encounters [4], [15]. In livestream commerce, such support may facilitate consumers' evaluation of product information and enable them to respond more readily to immediate purchase opportunities. When consumers receive appropriate assistance at the point of decision, the shopping process becomes more responsive and less cognitively demanding, which may increase their likelihood of making spontaneous purchase decisions. Accordingly, the following hypothesis is proposed:

H3c: Adaptive support positively influences impulse buying behavior in livestream commerce.

Taken together, the proposed relationships reflect the logic of the Stimulus-Organism-Response (S-O-R) framework, in which hedonic interaction, personalization, and adaptive support represent technological stimuli, trust represents a cognitive organismic state, and impulse buying behavior represents the behavioral response [7], [8]. In addition to examining how AI-driven interaction features contribute to trust and how trust influences impulse buying behavior, the proposed model examines whether these AI-driven interaction features exert direct effects on impulse buying behavior. This structure enables a more differentiated assessment of the roles of specific AI-enabled interaction capabilities in shaping consumer responses within livestream commerce environments.

2.2. Empirical research and research gap

Building upon the Stimulus-Organism-Response (S-O-R) framework, prior empirical studies have extensively examined consumer behavior in online and livestream commerce environments. These studies provide important insights into how environmental and technological factors influence consumers' psychological evaluations and behavioral responses. Nevertheless, several important limitations remain in the existing literature.

First, prior livestream commerce studies have primarily focused on environmental and situational characteristics such as interactivity, social presence, platform-related cues, and technology affordances [1], [2], [19], [20]. Although these studies demonstrate that technology-enabled shopping environments significantly influence consumer behavior, relatively limited attention has been devoted to the specific capabilities of AI-driven interaction and whether different AI interaction features generate distinct cognitive and behavioral responses.

Second, research on artificial intelligence in marketing and service contexts has demonstrated the growing role of AI-enabled systems in personalization, customer interaction, responsiveness, and service delivery [3], [4], [10], [15], [16], [22]. Related research further highlights the importance of personalization and data-driven customer interactions in improving the relevance and effectiveness of digital marketing experiences [13], [14], [23]. However, these capabilities have generally been examined as individual technological or service characteristics rather than jointly conceptualized as distinct dimensions of AI-driven interaction within a unified livestream commerce framework. Consequently, limited understanding exists regarding the relative roles of hedonic interaction, personalization, and adaptive support in shaping consumer responses in AI-enabled livestream environments.

Third, trust has consistently been recognized as an important determinant of consumer behavior in technology-mediated transactions because it helps consumers cope with uncertainty and facilitates decision-making in online environments [5], [6], [16]. Despite its established importance, comparatively limited attention has been devoted to trust as a cognitive organismic state within AI-enabled livestream commerce. As AI increasingly participates in product recommendations, customer assistance, and real-time interactions, understanding how different AI-driven interaction features contribute to trust and how trust subsequently influences consumer behavior becomes particularly important.

Fourth, existing research on impulse buying has emphasized environmental, affective, social, and situational drivers of spontaneous purchasing, including atmospheric cues, shopping enjoyment, social presence, scarcity, and time pressure [9], [17]-[20]. While these perspectives provide important explanations of impulse buying, comparatively less is known about how AI-specific interaction features contribute to spontaneous purchasing responses in livestream commerce. In particular, the direct effects of hedonic interaction, personalization, and adaptive support on impulse buying behavior remain insufficiently understood in increasingly AI-enabled shopping environments.

Taken together, the existing literature reveals three interrelated research gaps. First, insufficient attention has been devoted to conceptualizing AI-driven interaction as a multidimensional technological stimulus comprising distinct interaction features within the S-O-R framework. Second, the role of trust as a cognitive organismic state in AI-enabled livestream commerce remains insufficiently examined. Third, existing impulse buying research provides relatively limited understanding of how specific AI-driven interaction features are associated with spontaneous purchasing behavior in real-time livestream environments.

To address these gaps, this study integrates hedonic interaction, personalization, adaptive support, trust, and impulse buying behavior into a unified S-O-R framework [7], [8]. Specifically, the study contributes to the literature in three important ways. First, it advances the conceptualization of AI-driven interaction by distinguishing three dimensions: hedonic interaction, personalization, and adaptive support. Second, it positions trust as a cognitive organismic state and examines how the three AI-driven interaction features contribute to trust formation and how trust, in turn, influences impulse buying behavior. Third, it simultaneously examines the direct effects of the three AI-driven interaction features on impulse buying behavior, thereby providing a more differentiated explanation of consumer responses in AI-enabled livestream commerce.

Building upon the theoretical foundation and the identified research gaps, this study proposes the research model illustrated in Figure 1.

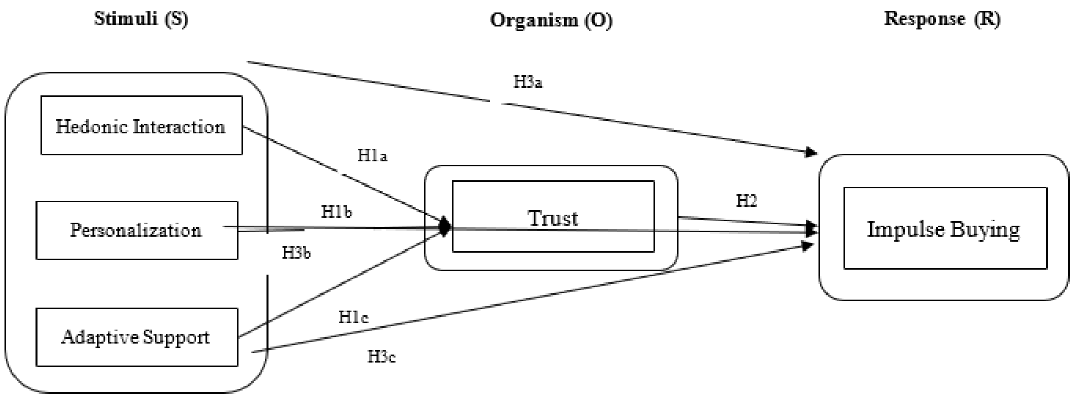

Figure 1. Proposed research model

Source: Authors' own development

3. RESEARCH METHODOLOGY

3.1. Research design

This study adopts a quantitative research approach to examine the relationships among AI-driven interaction features, trust, and impulse buying behavior in livestream commerce. Grounded in the Stimulus-Organism-Response (S-O-R) framework, the study conceptualizes hedonic interaction, personalization, and adaptive support as technological stimuli, trust as the organismic state, and impulse buying behavior as the behavioral response [7], [8].

Given the multidimensional nature of AI-driven interaction and the complexity of the proposed relationships, Structural Equation Modeling (SEM) was employed as the primary analytical technique. SEM is particularly appropriate for this study because it enables the simultaneous assessment of the measurement model and structural relationships among latent constructs while accounting for measurement error, thereby providing an appropriate analytical framework for testing the proposed research model [24], [25].

The study employs a cross-sectional survey designed to capture consumers' perceptions and experiences within livestream shopping environments. This approach is appropriate because livestream commerce represents a highly interactive and real-time digital context in which consumers are exposed to persuasive stimuli, personalized recommendations, and dynamic interaction mechanisms. Accordingly, the survey method enables the systematic investigation of how AI-enabled interaction features are associated with consumers' cognitive evaluations and behavioral responses during livestream shopping experiences.

Building upon the proposed research model, this study addresses the following research questions:

RQ1: How do AI-driven interaction features influence consumer trust in livestream commerce?

RQ2: Does trust significantly influence impulse buying behavior in livestream commerce?

RQ3: How do the effects of AI-driven interaction features differ in shaping trust and impulse buying behavior in livestream commerce?

3.2. Measurement development

To ensure theoretical rigor and measurement validity, all constructs in this study were operationalized using multi-item scales adapted from previously validated instruments in digital commerce, artificial intelligence, and consumer behavior research. Employing established measurement scales enhances content validity, conceptual consistency, and comparability with prior studies while reducing construct ambiguity in the context of AI-enabled livestream commerce.

Consistent with the proposed Stimulus-Organism-Response (S-O-R) framework, AI-driven interaction features were modeled as three distinct first-order constructs, namely hedonic interaction, personalization, and adaptive support, rather than as a single higher-order construct. This specification enables a more precise examination of how different AI-enabled interaction capabilities contribute to trust formation and impulse buying behavior in livestream commerce. Moreover, separating these dimensions captures the multidimensional nature of AI-driven interaction by distinguishing experiential, personalized, and functional aspects of AI-enabled consumer experiences.

Hedonic interaction reflects the extent to which AI-enabled interaction creates enjoyable, immersive, and entertaining shopping experiences during livestream sessions. The measurement items were adapted from prior studies on hedonic motivation and livestream shopping experiences [11], [12], [19].

Personalization refers to the capability of AI systems to provide customized recommendations, individualized content, and context-relevant shopping information based on consumers' preferences and behavioral patterns. The corresponding measurement items were adapted from established personalization research in digital marketing and online commerce [3], [13], [14].

Adaptive support reflects AI systems' capability to provide timely assistance, responsive communication, and dynamic problem-solving throughout livestream shopping sessions. The measurement items were adapted from prior studies examining AI-enabled service interactions and intelligent customer support [4], [15].

Trust was measured using established scales that capture consumers' perceptions of platform reliability, competence, integrity, and trustworthiness in online commerce [5], [6], [16].

Impulse buying behavior was measured using validated scales assessing spontaneous and unplanned purchasing behavior in online shopping environments [17], [18], [19], [20].

To ensure contextual appropriateness, all measurement items were slightly reworded to reflect AI-enabled livestream shopping while preserving their original conceptual meanings. Before formal data collection, the questionnaire was reviewed by experts in digital marketing and consumer behavior to evaluate item clarity, content validity, and contextual relevance. Subsequently, a pilot survey involving experienced livestream shoppers was conducted to refine wording and improve questionnaire readability.

All constructs were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The use of a consistent response format improves measurement reliability, facilitates respondents' understanding, and supports the robustness of SEM estimation.

The measurement specification adopted in this study is consistent with prior SEM-based research emphasizing multidimensional constructs in technology-enabled consumer behavior. Due to conference page limitations, only representative measurement items and their original sources are reported. Table 1 summarizes the construct operationalization, representative items, and corresponding measurement sources.

Table 1. Construct operationalization and measurement sources

Construct	Number of items	Sample item	Source
Hedonic Interaction (HI)	5	AI-enabled interaction during livestream shopping creates an enjoyable and immersive shopping experience.	[11], [12], [19]
Personalization (PE)	5	AI-generated recommendations effectively match my individual preferences and shopping needs.	[3], [13], [14]
Adaptive Support (AS)	5	AI systems provide timely and responsive assistance throughout the livestream shopping process.	[4], [15].
Trust (TR)	4	I believe that AI-enabled livestream shopping platforms are reliable and trustworthy.	[5], [6], [16]
Impulse Buying Behavior (IB)	5	I frequently make spontaneous purchasing decisions while participating in livestream shopping sessions.	[17]- [20]

3.3. Data collection and sample

Data were collected through an online survey targeting consumers with prior livestream shopping experience in Vietnam. Prior experience with livestream shopping was considered important because livestream commerce is characterized by real-time interaction, continuous consumer engagement, and immediate purchasing opportunities [1], [2], [19]-[21]. Rather than restricting the investigation to a single platform, the questionnaire asked respondents to identify the livestream platform they used most frequently, including TikTok, Shopee, Facebook, and other platforms. This cross-platform design enabled the study to capture consumer experiences across different livestream commerce environments rather than confining the analysis to a single platform.

The survey was conducted between January and February 2026 using a convenience sampling approach to reach consumers familiar with livestream shopping. A total of 543 responses were initially collected. The respondent pool was predominantly composed of younger consumers, with 76.4% aged 18-27 years, indicating a strong representation of Generation Z consumers. However, because respondents from other age groups were also represented, the study does not restrict its empirical interpretation exclusively to Generation Z.

The respondents demonstrated substantial exposure to livestream shopping environments. Specifically, 43.1% reported watching livestreams one to three times per week and 22.7% reported watching livestreams more than four times per week, whereas 34.3% reported watching livestreams less than once per week. Regarding platform usage, TikTok was the most frequently used platform (56.2%), followed by Shopee (25.4%) and Facebook (11.2%), while the remaining 7.2% reported other platforms. These characteristics indicate that the sample captured consumer experiences across multiple livestream platforms, with TikTok representing the dominant platform.

Prior to the main analysis, the collected responses were screened for completeness. Of the 543 responses initially collected, 63 questionnaires (11.6%) were excluded because of incomplete information, leaving 480 valid responses for analysis, equivalent to a valid response rate of 88.4%. The final sample was used for the subsequent measurement and structural model analyses.

Overall, the final sample provides an appropriate empirical basis for examining the relationships among perceived AI-driven interaction features, trust, and impulse buying behavior in livestream commerce. Its cross-platform composition allows the proposed relationships to be examined at the broader livestream commerce level rather than being attributed to the characteristics of a single platform.

3.4. Data analysis

The data were analyzed using SPSS and AMOS. The analysis was conducted in two main stages following established procedures for covariance-based structural equation modeling (CB-SEM) [24], [25]. First, confirmatory factor analysis (CFA) was performed to evaluate the measurement model. The assessment included standardized factor loadings, construct reliability, convergent validity, discriminant validity, and overall model fit. Construct reliability was evaluated using composite reliability (CR), while convergent validity was assessed using standardized factor loadings and average variance extracted (AVE). In accordance with commonly accepted guidelines, CR values of 0.70 or higher and AVE values of 0.50 or higher were considered indicative of satisfactory reliability and convergent validity [24]. Discriminant validity was assessed by comparing the square root of the AVE for each construct with its correlations with other constructs.

Model fit was evaluated using multiple goodness-of-fit indices, including the chi-square to degrees-of-freedom ratio (χ^2/df), Goodness-of-Fit Index (GFI), Tucker–Lewis Index (TLI), Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and PCLOSE. Because no single fit index provides a sufficient basis for evaluating model adequacy, these indices were considered jointly in assessing the overall fit of the measurement and structural models [24], [25].

Second, structural equation modeling (SEM) was employed to examine the hypothesized relationships among hedonic interaction, personalization, adaptive support, trust, and impulse buying behavior. The structural relationships were evaluated using standardized regression coefficients (β), critical ratios (C.R.), and corresponding significance levels. Hypotheses were considered supported when the estimated relationship was statistically significant and consistent with the hypothesized direction. The structural model was also evaluated using the same overall model-fit criteria applied in the measurement model assessment [24], [25].

This two-stage analytical procedure enabled the measurement properties of the constructs to be established before evaluating the hypothesized structural relationships among the latent variables.

3.5. Hypothesis testing

The proposed hypotheses were tested using structural equation modeling (SEM) in AMOS. Following the validation of the measurement model through confirmatory factor analysis (CFA), the structural model was estimated to examine the hypothesized relationships among hedonic interaction (HI), personalization (PE), adaptive support (AS), trust (TR), and impulse buying behavior (IB) [24], [25].

Hypothesis testing was based on the standardized path coefficients (β), critical ratios (C.R.), and corresponding *p*-values. A hypothesized relationship was considered statistically significant when the *p*-value was below 0.05 and the estimated coefficient was consistent with the predicted direction [24], [25]. Specifically, H1a–H1c examined the effects of hedonic interaction, personalization, and adaptive support on trust; H2 examined the effect of trust on impulse buying behavior; and H3a-H3c examined the direct effects of the three AI-driven interaction features on impulse buying behavior.

Accordingly, support for each hypothesis was determined by the statistical significance and direction of its corresponding structural path. The standardized coefficients were used to assess the relative magnitude of the relationships among the constructs, while the C.R. and *p*-values were used to evaluate their statistical significance.

4. DISCUSSION

4.1. Measurement model evaluation

Before testing the hypothesized structural relationships, Confirmatory Factor Analysis (CFA) was conducted to assess the adequacy of the measurement model. Following established recommendations for covariance-based structural equation modeling, measurement quality was evaluated in terms of model fit, standardized factor loadings, construct reliability, convergent validity, and discriminant validity [24], [25].

The measurement model demonstrated a satisfactory fit with the empirical data ($\chi^2 = 344.705$, df = 242, $\chi^2/df = 1.424$, GFI = 0.944, TLI = 0.979, CFI = 0.982, RMSEA = 0.030, and PCLOSE = 1.000). These indices indicate that the hypothesized measurement structure adequately represents the observed data according to commonly recommended SEM criteria [24], [25].

The standardized factor loadings for the individual measurement items are reported in Table 2. The loadings ranged from 0.693 to 0.790. Most indicators met or exceeded the recommended benchmark of approximately 0.70. Although TR2 exhibited a standardized loading of 0.693, this value was close to the recommended threshold and was retained because the Trust construct demonstrated satisfactory composite reliability and average variance extracted. Specifically, composite reliability (CR) ranged from 0.829 to 0.874, exceeding the recommended level of 0.70, while average variance extracted (AVE) ranged from 0.535 to 0.581, exceeding the recommended threshold of 0.50 [24], [25]. Collectively, these results provide evidence of satisfactory construct reliability and convergent validity.

Table 2. Standardized factor loadings, composite reliability, and average variance extracted

Construct	Item	Standardized loading	CR	AVE
Hedonic Interaction (HI)	HI1	0.743	0.874	0.581
	HI2	0.768		
	HI3	0.767		
	HI4	0.741		
	HI5	0.790		
Personalization (PE)	PE1	0.731	0.863	0.558
	PE2	0.743		
	PE3	0.775		
	PE4	0.737		
	PE5	0.747		
Adaptive Support (AS)	AS1	0.717	0.852	0.535
	AS2	0.709		
	AS3	0.735		
	AS4	0.770		
	AS5	0.724		
Trust (TR)	TR1	0.772	0.829	0.549
	TR2	0.693		
	TR3	0.742		
	TR4	0.752		
Impulse Buying Behavior (IB)	IB1	0.726	0.855	0.541
	IB2	0.730		
	IB3	0.715		
	IB4	0.752		
	IB5	0.755		

Source: Compiled from CFA results.

Discriminant validity was subsequently assessed using the Fornell-Larcker criterion. As presented in Table 3, the square root of the AVE for each construct exceeded its correlations with the other constructs. In addition, the maximum shared variance (MSV) for each construct was lower than its corresponding AVE. These results provide evidence that the five constructs exhibit adequate empirical distinctiveness [24], [25].

Table 3. Discriminant validity assessment

	CR	AVE	MSV	HI	IB	PE	AS	TR
HI	0.874	0.581	0.405	**0.762**				
IB	0.855	0.541	0.373	0.611	**0.736**			
PE	0.863	0.558	0.371	0.600	0.609	**0.747**		
AS	0.852	0.535	0.391	0.608	0.586	0.545	**0.731**	
TR	0.829	0.549	0.405	0.637	0.609	0.607	0.625	**0.741**

Source: Compiled from CFA results

Overall, the CFA results demonstrate satisfactory model fit, construct reliability, convergent validity, and discriminant validity. The measurement model therefore provides an adequate empirical basis for evaluating the hypothesized structural relationships in the subsequent SEM analysis

4.2. Structural model results

Following the satisfactory assessment of the measurement model, Structural Equation Modeling (SEM) was employed to test the hypothesized relationships among hedonic interaction, personalization, adaptive support, trust, and impulse buying behavior. The structural model retained a satisfactory overall fit with the empirical data (χ^2 = 344.705, df = 242, χ^2/df = 1.424, GFI = 0.944, TLI = 0.979, CFI = 0.982, RMSEA = 0.030, and PCLOSE = 1.000). These values satisfy the recommended criteria for covariance-based SEM [24], [25]. Although the global fit indices are identical to those obtained for the measurement model, the structural model differs in its specification by estimating the hypothesized directional relationships among the latent constructs. The estimated structural model is presented in Figure 2.

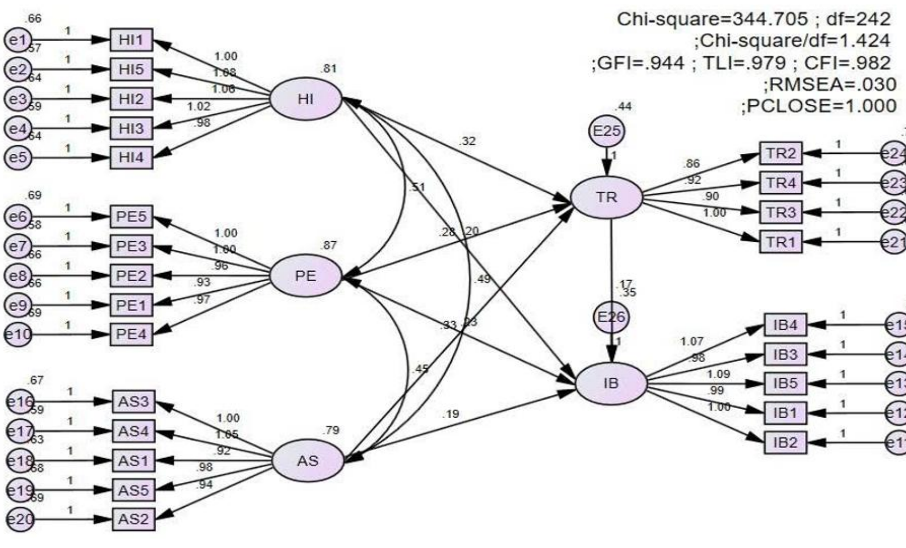

Figure 2. Structural Equation Modeling (SEM) Analysis

Source: Compiled from SEM analysis results

The hypothesized relationships were evaluated using standardized path coefficients (β), critical ratios (C.R.), and corresponding significance levels. As reported in Table 4, all seven hypothesized relationships were positive and statistically significant.

Hedonic interaction had a significant positive effect on trust (β = 0.294, C.R. = 4.606, $p < 0.001$), supporting H1a. Personalization also positively influenced trust (β = 0.266, C.R. = 4.472, $p < 0.001$), supporting H1b. Similarly, adaptive support had a significant positive effect on trust (β = 0.301, C.R. = 4.920, $p < 0.001$), supporting H1c. Among the three AI-driven interaction features, adaptive support exhibited the strongest standardized effect on trust, followed by hedonic interaction and personalization.

Trust had a significant positive effect on impulse buying behavior (β = 0.196, C.R. = 2.831, $p = 0.005$), thereby supporting H2. The three AI-driven interaction features also had significant positive direct effects on impulse buying behavior. Specifically, hedonic interaction positively influenced impulse buying behavior (β = 0.215, C.R. = 3.301, $p < 0.001$), supporting H3a. Personalization had a significant positive effect on impulse buying behavior (β = 0.255, C.R. = 4.132, $p < 0.001$), supporting H3b, while adaptive support also positively influenced impulse buying behavior (β = 0.194, C.R. = 3.068, $p = 0.002$), supporting H3c. Among these three direct effects, personalization exhibited the strongest standardized effect on impulse buying behavior.

Table 4. Structural Model Results and Hypothesis Testing

Hypothesis	Relationship	Estimate Standardized (β)	C.R.	p-value	Result
H1a	HI → TR	0.294	4.606	***	Supported
H1b	PE → TR	0.266	4.472	***	Supported
H1c	AS → TR	0.301	4.920	***	Supported
H2	TR → IB	0.196	2.831	.005	Supported
H3a	HI → IB	0.215	3.301	***	Supported
H3b	PE → IB	0.255	4.132	***	Supported
H3c	AS → IB	0.194	3.068	.002	Supported

Source: Compiled from SEM analysis results.

Overall, all seven hypothesized structural relationships were supported. The results reveal a differentiated pattern in the effects of AI-driven interaction features. Adaptive support exerted the strongest effect on trust, whereas personalization demonstrated the strongest direct effect on impulse buying behavior. Trust also significantly contributed to impulse buying behavior. These findings provide empirical support for the proposed structural relationships within the S-O-R framework and form the basis for their theoretical interpretation in the following discussion.

4.3. Discussion

This study provides empirical evidence on how AI-driven interaction features shape consumer trust and impulse buying behavior in livestream commerce within the Stimulus-Organism-Response (S-O-R) framework. The findings support all seven hypothesized relationships and reveal that hedonic interaction, personalization, and adaptive support contribute to both trust formation and impulse buying behavior, while trust itself also positively influences impulse buying. Taken together, these findings demonstrate that AI-enabled interaction is associated with both consumers' cognitive evaluations of the shopping environment and their behavioral responses.

First, the findings demonstrate that AI-driven interaction in livestream commerce is better understood as a multidimensional technological stimulus comprising hedonic interaction, personalization, and adaptive support rather than as a single technological capability. Consistent with previous research emphasizing the importance of interactivity and technology affordances in livestream commerce [1], [2], [19], all three interaction features significantly enhance consumer trust. Notably, adaptive support exhibits the strongest effect on trust ($\beta = 0.301$), followed by hedonic interaction ($\beta = 0.294$) and personalization ($\beta = 0.266$). This pattern suggests that, in AI-enabled livestream environments, trust is shaped not only by entertaining or personalized experiences but also by consumers' perceptions that the system can respond appropriately and provide timely assistance during the shopping process. This finding complements prior research on AI-enabled customer interaction and service technologies [4], [15], [16] by demonstrating the particular importance of responsive and supportive AI capabilities in the livestream commerce context.

Second, the findings confirm the important role of trust in explaining consumer behavior in AI-enabled livestream commerce. Trust has a significant positive effect on impulse buying behavior ($\beta = 0.196$, $p = 0.005$), consistent with established research showing that trust facilitates consumer transactions in technology-mediated environments [5], [6]. This finding is particularly relevant to livestream commerce, where consumers often make decisions in highly interactive and rapidly changing environments. Under such conditions, trust can provide consumers with greater confidence in the information, recommendations, and assistance delivered through AI-enabled interactions. The result therefore extends the application of the S-O-R framework by showing that the organismic state connecting technological stimuli and behavioral responses need not be exclusively affective; cognitive evaluations such as trust also constitute an important internal response to AI-enabled shopping environments [7], [8].

Third, the results reveal that AI-driven interaction features also exert significant direct effects on impulse buying behavior. Personalization demonstrates the strongest direct effect ($\beta = 0.255$), followed by hedonic interaction ($\beta = 0.215$) and adaptive support ($\beta = 0.194$). These findings are consistent with prior studies showing that personalized, interactive, and situational characteristics of digital shopping environments can stimulate spontaneous purchasing behavior [9], [17]-[20]. The relatively stronger effect of personalization suggests that impulse buying in AI-enabled livestream commerce may be particularly responsive to the perceived relevance of product recommendations and shopping information. When AI-supported interactions align product information with consumers' interests and immediate preferences, they may increase the salience and attractiveness of purchase opportunities, thereby facilitating more spontaneous purchase decisions.

An important pattern emerges when the effects on trust and impulse buying are considered together. Adaptive support has the strongest effect on trust, whereas personalization has the strongest direct effect on impulse buying behavior. This distinction suggests that different AI interaction features may perform different behavioral functions within the same livestream shopping environment. Adaptive support appears particularly important for strengthening consumers' confidence in AI-enabled interactions, whereas personalization appears more directly associated with stimulating immediate purchasing responses. Hedonic interaction contributes significantly to both outcomes, indicating that enjoyable interaction remains relevant but does not dominate either trust formation or impulse buying. This differentiated pattern provides a more nuanced understanding of AI-driven interaction than approaches that treat AI functionality as a homogeneous technological stimulus.

Overall, the findings extend existing livestream commerce research in two respects. First, they integrate AI-specific interaction features into the S-O-R framework and demonstrate that hedonic interaction, personalization, and adaptive support represent distinct technological stimuli with different relative effects on consumer responses. Second, they position trust as an important cognitive organismic state while simultaneously showing that AI-driven interaction features can directly stimulate impulse buying behavior. The results therefore suggest that consumer responses to AI-enabled livestream commerce arise from the combined influence of technological interaction quality, cognitive evaluation, and immediate behavioral stimulation. This perspective provides a more differentiated explanation of consumer decision-making in increasingly AI-mediated livestream shopping environments.

5. CONCLUSION

5.1. Conclusion

This study investigates how AI-driven interaction features shape consumer trust and impulse buying behavior in livestream commerce by integrating hedonic interaction, personalization, and adaptive support within the Stimulus-Organism-Response (S-O-R) framework. Rather than treating AI-enabled interaction as a homogeneous technological capability, the study conceptualizes it as a multidimensional set of interaction features that can generate distinct consumer responses in real-time digital shopping environments.

The empirical findings provide support for all hypothesized direct relationships. Hedonic interaction, personalization, and adaptive support each have significant positive effects on consumer trust and impulse buying behavior, while trust itself positively influences impulse buying behavior. Importantly, the relative strength of these effects differs across consumer responses. Adaptive support exhibits the strongest effect on trust, suggesting that responsiveness and effective AI-enabled assistance are particularly important for strengthening consumer confidence. In contrast, personalization demonstrates the strongest direct effect on impulse buying behavior, indicating that contextually relevant recommendations and individualized interactions are particularly influential in stimulating spontaneous purchase responses.

Overall, the study extends the application of the S-O-R framework to AI-enabled livestream commerce by demonstrating that different AI interaction features perform distinct behavioral functions. The findings provide a more differentiated understanding of how technological interaction, cognitive evaluation, and spontaneous purchasing responses coexist within increasingly AI-mediated livestream shopping environments.

5.2. Theoretical Implications

This study offers several theoretical contributions to the literature on AI-enabled livestream commerce and consumer behavior.

First, the study extends the S-O-R framework by conceptualizing AI-driven interaction as a multidimensional technological stimulus rather than treating technology as a homogeneous environmental factor [7], [8]. By distinguishing among hedonic interaction, personalization, and adaptive support, the findings demonstrate that individual AI-enabled interaction features differ in their relative influence on consumer responses. In particular, adaptive support has the strongest effect on trust, whereas personalization exhibits the strongest direct effect on impulse buying behavior. This differentiated pattern suggests that AI interaction capabilities should not be assumed to perform equivalent functions within the consumer decision process. The study therefore adds greater conceptual specificity to the stimulus component of the S-O-R framework in AI-mediated commerce.

Second, the study advances the application of trust within the S-O-R framework by positioning it as a cognitive organismic state through which consumers evaluate AI-enabled shopping interactions. Consistent with established research on trust in technology-mediated transactions [5], [6], the significant positive relationship between trust and impulse buying behavior indicates that cognitive evaluation remains relevant even in highly interactive and rapidly evolving livestream shopping environments. This finding broadens applications of S-O-R that predominantly emphasize affective organismic states by demonstrating the relevance of cognitive evaluation in explaining consumer responses to AI-enabled commercial environments.

Third, the study contributes to the impulse buying literature by demonstrating that hedonic interaction, personalization, and adaptive support each have significant direct effects on impulse buying behavior. Particularly noteworthy is the stronger direct effect of personalization, suggesting that the behavioral influence of AI in livestream commerce is not confined to entertainment or general interactivity. Instead, the ability of AI-enabled systems to increase the perceived relevance of recommendations and interactions appears especially important for spontaneous purchasing responses. This finding expands existing explanations of impulse buying by incorporating AI-specific technological stimuli into the livestream commerce context.

Finally, by integrating AI-driven interaction features, trust, and impulse buying behavior within a unified framework, this study connects research streams that have often examined AI-enabled interaction, trust, and spontaneous purchasing separately. The resulting framework provides a more differentiated theoretical account of consumer behavior in real-time, AI-mediated commerce and establishes a foundation for further research examining how emerging AI capabilities reshape consumer cognition and behavioral responses.

5.3. Practical Implications

The findings provide several practical implications for firms and platform operators seeking to design effective AI-enabled livestream commerce experiences.

First, firms should prioritize the development of adaptive AI capabilities that provide timely, responsive, and context-sensitive assistance during livestream shopping. Because adaptive support exhibits the strongest effect on trust, AI systems should be designed not merely to respond automatically but to provide relevant assistance that reflects consumers' immediate information and decision needs. Improving responsiveness and problem-solving capability may strengthen consumer confidence in AI-enabled interactions.

Second, personalization deserves particular managerial attention because it exhibits the strongest direct effect on impulse buying behavior. Livestream commerce platforms should therefore improve the relevance of AI-supported product recommendations, content presentation, and interaction prompts based on consumers' preferences and shopping context. Effective personalization can make purchase opportunities more salient and relevant while reducing the effort required to identify suitable products. At the same time, personalization practices should remain transparent and appropriate to the interaction context so that behavioral effectiveness does not come at the expense of consumer trust.

Third, hedonic interaction remains an important component of the AI-enabled livestream experience because it positively contributes to both trust and impulse buying behavior. Managers should therefore retain interactive and enjoyable elements that increase consumer involvement, while integrating them with functional AI capabilities such as personalization and adaptive assistance. The findings suggest that entertainment alone is unlikely to capture the full value of AI-enabled interaction; a more effective design combines enjoyment, relevance, and responsive support.

More broadly, the results suggest that firms should avoid adopting a one-dimensional AI strategy. Different AI interaction features appear to serve different managerial objectives: adaptive support is particularly relevant to trust formation, whereas personalization is more strongly associated with immediate impulse buying responses. Accordingly, AI-enabled livestream strategies should align specific technological capabilities with the consumer response that firms seek to strengthen rather than assuming that increasing the overall intensity of AI interaction will generate uniform behavioral outcomes.

5.4. Limitations and Future Research

Despite its contributions, this study has several limitations that provide opportunities for future research.

First, the study was conducted in Vietnam and focused on consumers with livestream shopping experience, with the final sample predominantly comprising younger consumers. Although this context is particularly relevant to the adoption of livestream commerce, the findings may not be directly generalizable to consumers in other cultural, institutional, or demographic settings. Consumer perceptions of AI-enabled interaction, trust, and impulse buying may differ across markets with varying levels of digital maturity, cultural orientations, and AI adoption. Future research could therefore conduct cross-cultural or cross-market comparisons to assess the generalizability of the proposed relationships.

Second, the study focuses on three AI-driven interaction features-hedonic interaction, personalization, and adaptive support-and trust as the principal cognitive organismic state. Livestream purchasing decisions, however, may also be influenced by other technological, social, and commercial stimuli. Price discounts, limited-time offers, scarcity cues, streamer characteristics, social presence, and promotional incentives may operate alongside AI-enabled interaction features in shaping impulse buying behavior. Future studies could incorporate these factors to develop a broader explanation of consumer responses in AI-enabled livestream environments.

Third, the present model examines the proposed direct structural relationships without explicitly testing boundary conditions that may alter their strength. Consumer characteristics such as AI familiarity, prior livestream shopping experience, technology readiness, and impulse buying tendency, as well as contextual characteristics such as product category and platform type, may influence responses to AI-driven interaction. Future research could examine these variables as moderators to identify when and for whom particular AI interaction features are most influential.

Fourth, the cross-sectional research design limits the extent to which temporal dynamics and causal changes in consumer responses can be established. Trust in AI-enabled systems may evolve through repeated interactions, while responses to personalization or adaptive assistance may also change as consumers gain experience with AI technologies. Longitudinal research could examine these developmental processes, while experimental designs could manipulate specific AI interaction features to provide stronger causal evidence regarding their effects on trust and impulse buying behavior.

Finally, the use of non-probability sampling limits the statistical generalizability of the findings. Future studies could employ probability-based sampling strategies, more heterogeneous consumer populations, or multi-platform samples to improve external validity. Comparative research across different livestream platforms could also determine whether platform-specific technological and social environments condition the relationships identified in this study.

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