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The Factors Influencing Impulsive Online Purchase Behavior in Beauty Products among University Students

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Abstract- In recent years, live-streaming e-commerce platforms represented by Douyin and Kuaishou have grown rapidly, fundamentally transforming Chinese consumer shopping patterns. Beauty and personal care products have emerged as among the most purchased categories by young consumers in this channel. However, the mechanisms through which live-streaming stimuli convert latent interest into impulsive purchasing actions remain theoretically underexplored. This study constructs an Extended Technology Acceptance Model (E-TAM) by integrating Platform Trust as an antecedent variable to examine how trust, perceived usefulness (PU), perceived ease of use (PEOU), and impulsive purchase intention (IPI) collectively shape actual purchase behavior (APB) among university students. A quantitative survey was administered to 325 undergraduate students at University A with prior live-streaming shopping experience, and the data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0. All six hypotheses were supported. Platform Trust significantly influenced both PU ($\beta = 0.320$) and PEOU ($\beta = 0.666$). PEOU positively predicted PU ($\beta = 0.522$). Both PU ($\beta = 0.493$) and PEOU ($\beta = 0.267$) significantly predicted IPI, which in turn exerted the strongest direct effect on APB ($\beta = 0.687$, $f^2 = 0.895$). The findings validate the applicability of the TAM in the live-streaming beauty commerce context and confirm a complete causal chain from trust establishment to behavioral realization. Practical implications for platform operators, beauty brands, and consumer educators are discussed.

Keywords: Platform Trust, Perceived Usefulness, Perceived Ease of Use, Impulsive Purchase Intention, Actual Purchase Behavior, Live-streaming E-commerce.

I. Introduction

Since its emergence in China around 2016, live-streaming e-commerce has evolved from a novelty into a dominant retail channel. Platforms such as Douyin, Taobao Live, and Kuaishou generate hundreds of billions of yuan in annual gross merchandise value (Quong et al., 2018). Unlike traditional e-commerce, live-streaming combines real-time video demonstrations, interactive communication between hosts and viewers, and time-sensitive promotional mechanisms such as flash sales and exclusive discounts. These features create a highly immersive shopping environment that has proven particularly effective at stimulating impulsive purchase behavior.

Beauty and personal care products represent one of the highest-performing categories in this environment. For university students—who are tech-savvy, socially connected, and sensitive to trends—live-streaming platforms have become the primary discovery and purchase channel for cosmetics, skincare, and related products. Recent studies have shown that a substantial proportion of university students make unplanned beauty product purchases while watching live streams, often triggered by streamer recommendations, limited-time offers, or interactive demonstrations (Cai & Jonjoubsong, 2025; Cui et al., 2024).

Despite the growing commercial significance of this phenomenon, the theoretical understanding of its underlying mechanisms remains incomplete. Two critical gaps exist in the current literature. First, most studies examining impulsive purchasing in live-streaming contexts focus on emotional or hedonic stimuli without adequately accounting for the role of platform-level institutional factors such as trust Xu, H., & Mohd Kamil, N. L. (2025). Artificial Intelligence Literacy and Ethical Digital Governance: Pathways of Multi-Stakeholder Collaboration and Value Alignment. Journal of Advances in Humanities Research, 4(3), 61–89. https://doi.org/10.56868/jadhur.v4i3.310. Consumers shopping through live streams cannot physically examine products, and the transaction depends heavily on their confidence in the platform's security, seller reputation, and dispute resolution capabilities. Second, existing research often treats impulsive purchase intention as the terminal outcome variable, neglecting to empirically examine the subsequent transition from intention to actual purchase behavior—a gap that Peña-García et al. (2020) have explicitly identified as the "intention-behavior gap."

This study addresses both gaps by constructing an Extended Technology Acceptance Model (E-TAM) that positions Platform Trust as the initiating variable in a five-construct causal chain: Platform Trust → Perceived

Usefulness / Perceived Ease of Use → Impulsive Purchase Intention → Actual Purchase Behavior. The model is empirically tested using PLS-SEM with a sample of 325 undergraduate students, providing both theoretical validation and actionable insights for practitioners operating in the live-streaming beauty market.

1.1 Research Objectives

1. To examine the influence of Platform Trust on Perceived Usefulness and Perceived Ease of Use;
2. To investigate the effect of Perceived Ease of Use on Perceived Usefulness;
3. To analyze the impact of Perceived Usefulness and Perceived Ease of Use on Impulsive Purchase Intention;
4. To determine whether Impulsive Purchase Intention significantly predicts Actual Purchase Behavior.

1.2 Research Hypotheses

H1: Platform Trust has a significant positive influence on Perceived Usefulness.
H2: Platform Trust has a significant positive influence on Perceived Ease of Use.
H3: Perceived Ease of Use has a significant positive influence on Perceived Usefulness.
H4: Perceived Usefulness has a significant positive influence on Impulsive Purchase Intention.
H5: Perceived Ease of Use has a significant positive influence on Impulsive Purchase Intention.
H6: Impulsive Purchase Intention has a significant positive influence on Actual Purchase Behavior.

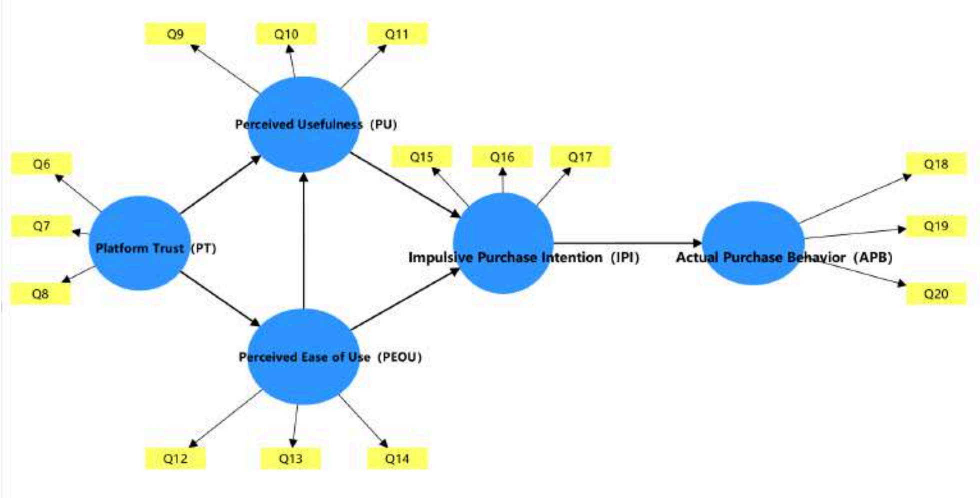

Figure 1. Research Framework (Extended Technology Acceptance Model (TAM), adapted from Davis, 1989, with the addition of trust)

II. Literature Review

2.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model, originally proposed by Davis (1989), posits that technology adoption is primarily determined by two cognitive constructs: Perceived Usefulness (PU)—the degree to which a user believes that using the system will enhance performance—and Perceived Ease of Use (PEOU)—the degree to which a user expects the system to be free of effort. Davis demonstrated that PEOU is a direct antecedent of PU, and both constructs jointly predict behavioral intention to use, which in turn predicts actual system usage. Subsequent studies (Venkatesh & Davis, 2000; Venkatesh et al., 2003) extended TAM by incorporating social influence, cognitive instrumental processes, and facilitating conditions.

TAM has been applied extensively in online consumer behavior research. Koufaris (2002) demonstrated that PU and PEOU, alongside flow and shopping enjoyment, predict purchase intention in online retail settings. Childers et al. (2001) expanded the operationalization of PU in shopping contexts to encompass both utilitarian efficiency and hedonic enjoyment. The model's parsimony and empirical robustness make it an ideal theoretical foundation for examining technology-mediated impulsive purchasing in live-streaming environments, where both functional utility and ease of interaction play critical roles.

2.2 Platform Trust in E-Commerce

Trust is a fundamental mechanism for reducing uncertainty in digital transactions. Mayer, Davis, and Schoorman (1995) proposed a multidimensional model of organizational trust comprising three components: ability (the trustee's competence), benevolence (the trustee's orientation toward the trustor's well-being), and integrity (the trustee's adherence to accepted principles). Gefen, Karahanna, and Straub (2003) extended this framework to e-commerce, demonstrating that platform trust reduces the social complexity and perceived risk inherent in online interactions, thereby positively influencing both PU and PEOU.

In the live-streaming context, Platform Trust encompasses two distinct dimensions: institutional trust, referring to the platform's structural safeguards such as payment security, after-sales protection, and quality standards; and interpersonal trust, referring to consumers' confidence in the streamer's expertise, authenticity, and recommendations. McKnight et al. (2002) found that structural assurance—a form of institutional trust—directly reduces perceived cognitive burden, thereby enhancing PEOU. Wongkitrungrueng and Assarut (2020) provided empirical evidence in live-streaming settings that trust in streamers and platforms significantly influences purchase behavior through enhanced engagement and reduced perceived risk.

2.3 Impulsive Purchase Intention and Actual Purchase Behavior

Impulse buying was conceptualized by Rook (1987) as a spontaneous, powerful, and emotionally charged desire to buy immediately. Beatty and Ferrell (1998) identified "felt urge"—the immediate, intense desire to purchase—as the direct precursor to impulsive buying action, with browsing behavior, positive affect, and time availability as key antecedents. In the live-streaming environment, Floh and Madlberger (2013) demonstrated that atmospheric cues such as visual appeal, scarcity signals, and social proof directly stimulate impulse buying tendency.

Critically, this study distinguishes between Impulsive Purchase Intention and Actual Purchase Behavior, treating them as separate constructs connected by a directional path. Ajzen's (1991) Theory of Planned Behavior (TPB) establishes that behavioral intention is the most proximal predictor of actual behavior. However, Peña-García et al. (2020) noted that in online environments, an intention-behavior gap may emerge due to external friction factors such as technical difficulties, payment complications, or cognitive dissonance post-stimulus. By measuring APB independently, this study directly tests whether the intention-to-behavior conversion holds in the live-streaming beauty context.

III. Materials and Methods

3.1 The Population / Sample Group

This study adopted a quantitative, cross-sectional survey design. The target population comprised all undergraduate students at University A , Guilin, China, totaling approximately 9,000 students, of whom approximately 70% are female—a demographic profile well-aligned with the beauty product focus of this study. Simple random sampling was employed via questionnaire links distributed through the college's official WeChat groups, ensuring that all eligible students across all year levels had an equal probability of participation.

Eligibility was restricted to students with prior live-streaming shopping experience for beauty products, confirmed through a screening question at the survey's outset. A total of 325 valid responses were retained after data cleaning. This sample size substantially exceeds the critical threshold of 200 recommended for PLS-SEM analysis (Boomsma, 1982; Hoelter, 1983) and falls within Comrey and Lee's (1992) "good" category of 300–500 for factor analysis.

3.2 Research Instruments

The questionnaire comprised two sections: (1) demographic information and (2) measurement items for the five constructs. All construct items were adapted from previously validated scales: Platform Trust items were adapted from Gefen et al. (2003) and McKnight et al. (2002); PU and PEOU items followed Davis (1989); IPI items drew from Beatty and Ferrell (1998) and Rook (1987); APB items were adapted from Peña-García et al. (2020). All items were measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The instrument was validated for content validity by five academic experts using the Item-Objective Congruence (IOC) index, with all items scoring above 0.60. Pilot testing with 30 respondents confirmed internal consistency, with all Cronbach's Alpha coefficients exceeding 0.80.

3.3 Data Analysis

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0. PLS-SEM was selected for its superior statistical power with complex models and its suitability for theory extension research. The analysis proceeded in two stages: (1) measurement model evaluation, assessing reliability (Cronbach's Alpha, rho_c), convergent validity (Average Variance Extracted, AVE), and discriminant validity (Fornell-Larcker criterion and HTMT ratio); and (2) structural model evaluation, examining path coefficients, effect sizes (f^2), coefficient of determination (R^2), predictive relevance (Q^2), and indirect effects via bootstrapping with 5,000 resamples.

IV. Results

4.1 Sample Characteristics

Table 1. Characteristics of the Respondents (N = 325)

Characteristics	Category	Frequency (n)	Percentage (%)
Gender	Male	83	25.54
	Female	242	74.46
Year of Study	Freshman (Year 1)	147	45.23
	Sophomore (Year 2)	57	17.54
	Junior (Year 3)	76	23.38
	Senior (Year 4)	45	13.85
Academic Major	Arts / Humanities	105	32.31
	Science / Engineering	60	18.46
	Management / Business	51	15.69
	Others	109	33.54
Monthly Disposable Income	≤ 1,500 RMB	189	58.15
	1,501 – 2,500 RMB	99	30.46
	2,501 – 4,000 RMB	17	5.23
	≥ 4,001 RMB	20	6.15
Live-stream Viewing (per week)	Rarely (< 1 hour)	206	63.38
	1 – 2 hours	80	24.62
	3 – 5 hours	24	7.38
	≥ 6 hours	15	4.62

Data Source: *The authors used SPSS 20 software to calculate the collected data.*

Among the 325 respondents, 242 (74.46%) were female and 83 (25.54%) were male, consistent with the college's approximately 7:3 female-to-male enrollment ratio. In terms of year level, Year 1 (Freshman) students accounted for the largest proportion at 45.23% (n = 147), followed by Year 3 (Junior) at 23.38% (n = 76), Year 2 (Sophomore) at 17.54% (n = 57), and Year 4 (Senior) at 13.85% (n = 45). Regarding academic major, Arts/Humanities students comprised 32.31% (n = 105), Science/Engineering 18.46% (n = 60), Management/Business 15.69% (n = 51), and Others 33.54% (n = 109). For monthly disposable income, 58.15% earned ≤ 1,500 RMB and 30.46% earned 1,501–2,500 RMB, reflecting the economic constraints typical of Chinese university students. Regarding live-streaming viewing frequency, 63.38% (n = 206) reported rarely watching (< 1 hour per week), 24.62% (n = 80) watched 1–2 hours, 7.38% (n = 24) watched 3–5 hours, and 4.62% (n = 15) watched ≥ 6 hours per week.

4.2 Measurement Model Results

Table 2. Standardized Factor Loadings of Measurement Items

Item	Construct	Loading
Q6	Platform Trust (PT)	0.831
Q7	Platform Trust (PT)	0.911
Q8	Platform Trust (PT)	0.862
Q9	Perceived Usefulness (PU)	0.926
Q10	Perceived Usefulness (PU)	0.935
Q11	Perceived Usefulness (PU)	0.921
Q12	Perceived Ease of Use (PEOU)	0.885
Q13	Perceived Ease of Use (PEOU)	0.882
Q14	Perceived Ease of Use (PEOU)	0.797

Q15	Impulsive Purchase Intention (IPI)	0.914
Q16	Impulsive Purchase Intention (IPI)	0.935
Q17	Impulsive Purchase Intention (IPI)	0.872
Q18	Actual Purchase Behavior (APB)	0.876
Q19	Actual Purchase Behavior (APB)	0.879
Q20	Actual Purchase Behavior (APB)	0.945

Data Source: *Calculated by the authors using SmartPLS 4 software.*

Table 2 presents the outer loadings for all measurement items. All standardized factor loadings ranged from 0.797 to 0.945, exceeding the recommended threshold of 0.708 (Hair et al., 2019), indicating that each item adequately represented its corresponding latent variable.

Table 3. Reliability and Average Variance Extracted (AVE) of Latent Variables

Construct	Cronbach's α	rho_a	rho_c	AVE
Platform Trust (PT)	0.837	0.844	0.902	0.755
Perceived Usefulness (PU)	0.919	0.920	0.949	0.860
Perceived Ease of Use (PEOU)	0.816	0.821	0.891	0.733
Impulsive Purchase Intention (IPI)	0.892	0.893	0.933	0.823
Actual Purchase Behavior (APB)	0.883	0.888	0.928	0.811

Data source: The data was calculated and processed by the author using SmartPLS 4.0 based on the collected data.

Table 3 presents the construct-level reliability and convergent validity statistics. All Cronbach's Alpha values ranged from 0.816 to 0.919, and composite reliability (rho_c) ranged from 0.891 to 0.949, both exceeding the threshold of 0.70. All AVE values exceeded 0.50 (range: 0.733–0.860), confirming convergent validity.

Table 4. Discriminant Validity — Fornell-Larcker Criterion (diagonal = √AVE) and HTMT (in parentheses)

	APB	IPI	PEOU	PT	PU
APB	0.901				
IPI	0.687 (0.770)	0.907			
PEOU	0.581 (0.684)	0.629 (0.737)	0.856		
PT	0.541 (0.633)	0.572 (0.660)	0.666 (0.805)	0.869	
PU	0.652 (0.721)	0.689 (0.760)	0.736 (0.848)	0.668 (0.758)	0.927

Data source: *The data was calculated and processed by the author using SmartPLS 4.0 based on the collected data.*

Discriminant validity was assessed using the Fornell-Larcker criterion and HTMT ratios. As shown in Table 4, the square root of AVE for each construct (diagonal values) exceeded its correlations with all other constructs, satisfying the Fornell-Larcker criterion. All HTMT values were below 0.85 (maximum = 0.848 between PEOU and PU), confirming adequate discriminant validity.

Structural Model Results

Table 5. PInternal Model VIF

Path	VIF
IPI -> APB	1.000
PEOU -> IPI	2.179
PEOU -> PU	1.798
PT -> PEOU	1.000
PT -> PU	1.798
PU -> IPI	2.179

Data source: *The data was calculated and processed by the author using SmartPLS 4.0 based on the collected data.*

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Table 6. Path Analysis Results (Bootstrapping, n = 5,000)

Hypothesis	Path	β (O)	Mean (M)	STDEV	T-Statistic	p-value	f²	Decision
H1	PT → PU	0.320	0.318	0.069	4.651	< 0.001	0.142	Supported
H2	PT → PEOU	0.666	0.666	0.047	14.138	< 0.001	0.798	Supported
H3	PEOU → PU	0.522	0.525	0.062	8.388	0.003	0.377	Supported
H4	PU → IPI	0.493	0.491	0.091	5.442	< 0.001	0.226	Supported
H5	PEOU → IPI	0.267	0.269	0.088	3.018	0.003	0.066	Supported
H6	IPI → APB	0.687	0.688	0.041	16.884	< 0.001	0.895	Supported

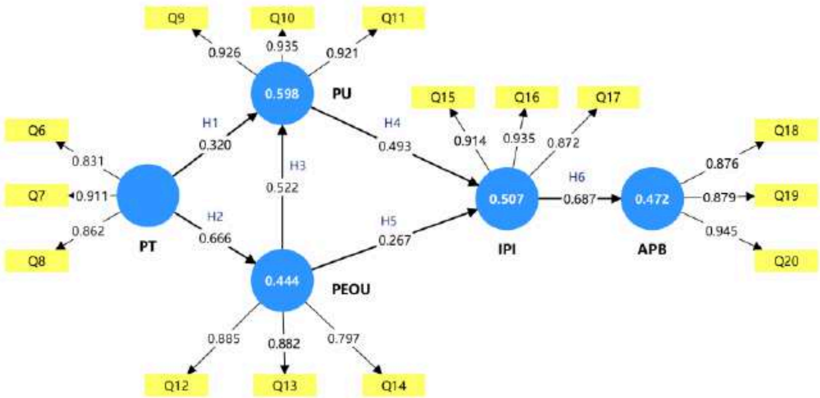

Figure 2. Structural equation diagram
Data source: The data was calculated and processed by the author using SmartPLS 4.0 based on the collected data.

Before path analysis, multicollinearity was assessed using the Variance Inflation Factor (VIF). All VIF values ranged from 1.000 to 2.179, well below the threshold of 3.0 (Hair et al., 2019), confirming no multicollinearity concerns. Table 6 presents the path analysis results from bootstrapping (5,000 resamples). All six hypotheses were supported.

Table 7. Coefficient of Determination (R^2) and Predictive Relevance (Q^2)

Endogenous Variable	R^2	Adjusted R^2	Q^2predict	RMSE	MAE
Perceived Usefulness (PU)	0.598	0.596	0.440	0.753	0.538
Perceived Ease of Use (PEOU)	0.444	0.442	0.438	0.755	0.580
Impulsive Purchase Intention (IPI)	0.507	0.504	0.318	0.832	0.622
Actual Purchase Behavior (APB)	0.472	0.471	0.252	0.869	0.702

Data source: *The data was calculated and processed by the author using SmartPLS 4.0 based on the collected data.*

All R^2 values exceeded the "large effect" criterion of 0.33 (Hair et al., 2019), with PU achieving the highest explanatory power ($R^2 = 0.598$). All Q^2predict values exceeded 0.25 (range: 0.252–0.440), with PEOU and PU exceeding 0.40, demonstrating strong external predictive relevance. The RMSE and MAE values were consistently low (< 0.87), confirming the model's practical predictive accuracy.

Table 8. Indirect Effects Analysis (Bootstrap, n = 5,000)

Mediation Path	β (O)	Mean (M)	STDEV	T-Statistic	p-value
PT → PEOU → PU	0.348	0.351	0.054	6.447	< 0.001
PT → PEOU → IPI	0.178	0.179	0.059	2.998	0.003
PT → PU → IPI	0.158	0.154	0.038	4.142	< 0.001

PT → PEOU → PU → IPI	0.171	0.173	0.045	3.819	< 0.001
PU → IPI → APB	0.339	0.339	0.069	4.894	< 0.001
PEOU → IPI → APB	0.183	0.186	0.063	2.902	0.004
PT → PEOU → IPI → APB	0.122	0.124	0.043	2.853	0.004
PT → PU → IPI → APB	0.108	0.107	0.028	3.840	< 0.001
PT → PEOU → PU → IPI → APB	0.118	0.119	0.033	3.557	< 0.001
PEOU → PU → IPI	0.257	0.258	0.059	4.351	< 0.001
PEOU → PU → IPI → APB	0.177	0.178	0.044	4.056	< 0.001

Data source: *The data was calculated and processed by the author using SmartPLS 4.0 based on the collected data.*

The indirect effects analysis (Table 8) confirmed significant mediation chains across all pre-specified paths ($p < 0.01$). The indirect effect of PT → PEOU → PU ($\beta = 0.348$, $T = 6.447$) was stronger than the direct path PT → PU ($\beta = 0.320$), indicating that Platform Trust primarily enhances perceived usefulness through an ease-of-use mediation pathway. Among the three indirect paths from PT to APB, PT → PEOU → IPI → APB yielded the strongest total indirect effect ($\beta = 0.122$, $T = 2.853$), as the exceptionally large PT → PEOU coefficient ($\beta = 0.666$) generates a higher cumulative effect than the alternative paths PT → PU → IPI → APB ($\beta = 0.108$) and PT → PEOU → PU → IPI → APB ($\beta = 0.118$). These multi-level mediation results enrich the theoretical understanding of the mechanisms through which institutional trust ultimately translates into purchasing behavior.

V. Discussion

5.1 Platform Trust as the Foundation of Cognitive Perception

The strong effect of Platform Trust on PEOU ($\beta = 0.666$, $f^2 = 0.798$) represents the most powerful direct relationship in the entire model and exceeds comparable findings in previous e-commerce research. Lu et al. (2011) reported a coefficient of 0.54 in mobile payment contexts, while Gefen et al. (2003) reported 0.51 in online bookstores. The amplified effect observed in this study can be attributed to the distinctive characteristics of live-streaming e-commerce: the real-time, interactive nature of live streams—where hosts immediately demonstrate products, answer questions, and facilitate purchases—substantially reduces the learning curve for platform navigation. When students trust the platform's institutional safeguards, they approach the interface with reduced cognitive vigilance, perceiving it as more intuitive and easier to use.

The finding that the indirect path PT → PEOU → PU ($\beta = 0.348$) exceeded the direct PT → PU path ($\beta = 0.320$) carries important theoretical implications. It suggests that Platform Trust enhances perceived usefulness primarily by first easing the perceptual burden of using the system, rather than through a direct "belief" mechanism. This sequential process—trust reduces cognitive load, which in turn allows users to more fully perceive functional value—represents a more nuanced understanding of the trust-TAM relationship than previously documented.

5.2 Cognitive Antecedents of Impulsive Purchase Intention

A notable contribution of this study is demonstrating that impulsive purchasing in live-streaming contexts is not purely emotion-driven, but is substantially shaped by rational cognitive perceptions. Perceived Usefulness exerted a stronger direct effect on IPI ($\beta = 0.493$) than PEOU ($\beta = 0.267$), suggesting that the perceived functional value of the live-streaming experience—its capacity to deliver meaningful product information, comparison capabilities, and exclusive benefits—is the primary cognitive driver of purchase impulse. This finding extends Davis's (1989) original TAM, which was developed in workplace technology contexts, into the hedonic and impulsive domain of consumer behavior.

The significant direct effect of PEOU on IPI ($\beta = 0.267$) is particularly noteworthy, as classic TAM typically treats PEOU's effect on behavioral intention as indirect through PU (Venkatesh & Davis, 2000). Three contextual factors specific to this study's setting may explain this deviation: (1) the time-sensitive nature of live-streaming promotions demands rapid decision-making, making ease of use directly critical for impulse conversion; (2) the predominantly low-frequency user profile (63.38%) means that many respondents are less experienced with live-streaming platforms, making ease of use a direct barrier or enabler of purchase intent; and (3) beauty products require access to substantial information (ingredients, skin-type suitability, usage demonstrations), and easy-to-navigate platforms directly reduce information acquisition friction, stimulating impulsive interest.

5.3 The Intention-to-Behavior Conversion

The exceptional path coefficient from IPI to APB ($\beta = 0.687$, $f^2 = 0.895$) confirms that once purchase intention is formed in the live-streaming context, it converts to actual behavior with remarkably high probability. This finding aligns with Ajzen's (1991) TPB while also addressing Peña-García et al.'s (2020) concern about the intention-behavior gap. In the live-streaming environment, the gap may be substantially narrowed by design: one-click purchasing, integrated payment systems, and the psychological urgency created by countdown timers and limited stock notifications minimize the friction between intention formation and behavioral completion. Platforms have effectively engineered out many of the cognitive checkpoints that might otherwise interrupt the purchase process.

VI. Conclusion

This study makes three principal contributions. Theoretically, it extends the Technology Acceptance Model by establishing Platform Trust as a formal antecedent variable and by empirically demonstrating a complete five-construct causal chain from trust establishment to actual purchase completion in the live-streaming beauty commerce context. The model's strong explanatory power across all endogenous variables (R^2 ranging from 0.444 to 0.598) and the support of all six hypotheses validate the E-TAM's applicability in this emerging retail context.

Empirically, the study contributes the first comprehensive PLS-SEM analysis of beauty product impulsive purchasing in Chinese live-streaming e-commerce using a university student sample. The finding that PEOU has a direct effect on IPI—beyond its indirect effect through PU—represents a context-specific insight that enriches the theoretical understanding of TAM applications in hedonic commerce settings. The indirect effects analysis further reveals that Platform Trust operates primarily through a sequential mediation chain (PT → PEOU → PU → IPI → APB), underscoring the importance of ease-of-use as the critical bridge between institutional trust and cognitive utility.

Practically, this study offers four recommendations. First, live-streaming platform operators should prioritize trust-building infrastructure, including transparent dispute resolution mechanisms, verified streamer certification programs, and prominent display of consumer protection policies, as these directly enhance both usability perceptions and perceived functional value. Second, interface optimization should focus on low-frequency users, who represent the majority of the student market and for whom ease of use is both a direct predictor of impulse intention and a necessary condition for trust-enhanced utility. Third, beauty brands should invest in information-rich, demonstrably useful live content—detailed ingredient explanations, real-time skin compatibility testing, and comparative before-and-after demonstrations—to maximize perceived usefulness. Fourth, conversion strategies such as limited-time pricing, embedded one-click purchasing, and instant post-purchase confirmation should be deployed immediately upon intention formation, capitalizing on the model's demonstration that the intention-to-behavior conversion is highly probable once IPI is triggered.

Future research should expand the sample to include students from multiple institutions across China and different product categories to test the model's generalizability. Longitudinal designs would enable the examination of how repeated live-streaming exposure modifies the trust-perception-intention-behavior relationships. The incorporation of additional variables—such as social influence, hedonic motivation, and post-purchase satisfaction—could further enrich the theoretical framework. Mixed-methods approaches combining quantitative SEM with qualitative interviews would provide deeper insight into the psychological mechanisms underlying impulsive purchasing in this context.

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